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# **Learning Curves and Engineering Assessment of Emerging Energy Technologies: Onshore Wind**

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The University of Edinburgh

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## Abstract

Sustainable energy systems require deployment of new technologies to help tackle the challenges of climate change and ensuring energy supplies. Future sources of energy are less economically competitive than conventional technologies, but there is the potential for cost reduction. Tools for modelling technological change are important for assessing the deployment potential of early-stage technologies. Learning curves are a tool for assessing and forecasting cost reduction of a product achieved through experience from cumulative production. They are often used to assess technological improvements, but have a number of limitations for emerging energy technologies. Learning curves are aggregate in nature, representing overall cost reduction gained from learning-by-doing. However, they do not identify the actual factors behind the cost reduction. Using the case study of onshore wind energy, this PhD study focuses on combining *learning curves* with *engineering assessment* methods for improved methods of assessing and managing technical change for emerging energy technologies. A third approach, *parametric modelling*, provides a potential means to integrate the two methods.

## Lay Summary

The challenges faced by the energy sector of meeting rising demand in many countries as traditional sources get exhausted, and fighting climate change require new sources of electricity. Renewable sources of electricity such as wind energy are relatively new and more expensive in the early stages of their inception compared to established traditional sources of electricity such as coal and gas. However, these have the potential to have their cost reduced as they get more established in the market. Methods of measuring costs and the potential for cost reduction are important for these early stage electricity sources. One way of measuring cost reduction potential is the use of *learning curves* which are based on the idea that overall costs of an energy source will reduce with experience of using it. Although it has been found useful for many products for assessing past cost and predicting future costs, the use of this method has limitations and challenges for new energy sources. This PhD focuses on finding ways of improving the use of the learning curve method by combining it with other ways of measuring cost of energy sources using engineering based methods.

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To my daughter Tanya- you can do it.

Finally, Mako Marcus my husband for all the care, encouragement, tolerance and sacrifices- you are the best.

This work is dedicated to Tamara and the memory of my mother Florence.

## Declaration

This thesis is a presentation of my original work which has not been submitted for any other degree or professional qualification.

Signed

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Date

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## Nomenclature

|             |                                     |
|-------------|-------------------------------------|
| $A$         | Rotor swept area                    |
| $A_{BP}$    | Bedplate area                       |
| $A_{LSS}$   | Low speed shaft area                |
| $A_{NCLAD}$ | Nacelle cladding area               |
| $\alpha$    | Experience index                    |
| $\beta$     | Knowledge stock experience index    |
| $b$         | Experience Index                    |
| $B$         | Number of blades                    |
| $C_D$       | Drag Coefficient                    |
| $C_t$       | Unit cost at time t                 |
| $C_0$       | Cost of first unit                  |
| $C_p$       | Coefficient of performance          |
| $D$         | Turbine diameter                    |
| $D_t$       | Tower top diameter                  |
| $D_{tb}$    | Tower bottom diameter               |
| $F_A$       | Aerofoil weight service factor      |
| $F_{BC}$    | Blade connection service factor     |
| $F_{BP}$    | Bedplate service factor             |
| $F_{CL}$    | Cyclic load service factor          |
| $F_G$       | Generator calibrations factor       |
| $F_{GD}$    | Gearbox design service factor       |
| $F_{HC}$    | Hub control type service factor     |
| $F_{HG}$    | Hub geometry service factor         |
| $F_{HL}$    | Hub load service factor             |
| $F_{LSS}$   | Low speed shaft service factor      |
| $F_{RC}$    | Rotor control service factor        |
| $F_S$       | Gearbox service factor              |
| $F_W$       | Gearbox stage volume service factor |
| $\delta$    | Tower wall thickness                |
| $g$         | Gravitational force                 |
| $H$         | Hub height                          |
| $\eta$      | Efficiency                          |
| $K_t$       | Knowledge stock at time t           |
| $\lambda$   | Tip Speed Ratio                     |
| $\lambda_d$ | Design (optimum) tip speed ratio    |
| $L_{BP}$    | Bedplate length                     |
| $L_{LSS}$   | Low speed shaft length              |
| $L_{const}$ | Constant losses                     |
| $L_{lin}$   | Linear losses                       |
| $L_{quad}$  | Quadratic Losses                    |
| $M_B$       | Blade bending moment                |
| $M_b$       | Tower foot bending moment           |
| $M_{LSS}$   | Low speed shaft bending moment      |
| $P_r$       | Rated power                         |
| $P_{ratio}$ | Power ratio                         |



---

|                   |   |
|-------------------|---|
| $Q_r$             | Rated torque                                      |
| $Q_{LSS}$         | Low speed shaft torque                            |
| $Q_S$             | Gear stage output torque                          |
| $q_t$             | Cumulative production at time t                   |
| $R$               | Turbine Radius                                    |
| $R_t$             | Tower radius                                      |
| $r$               | Turbine relative diameter                         |
| $\rho_a$          | Air density                                       |
| $\rho_{BC}$       | Blade connection material density                 |
| $\rho_H$          | Hub material density                              |
| $\rho_{SP}$       | Spar material density                             |
| $\rho_s$          | Steel density                                     |
| $\rho_{LSS}$      | Low speed shaft material density                  |
| $\rho_t$          | Tower material density                            |
| $S$               | Solidity  |
| $\sigma_{admin}$  | Admissible strength                               |
| $\sigma_{BC}$     | Blade connection admissible strength              |
| $\sigma_e$        | Endurance limit                                   |
| $\sigma_H$        | Hub material admissible strength                  |
| $\sigma_{SP}$     | Spar material admissible strength                 |
| $\sigma_S$        | Steel admissible strength                         |
| $\sigma_{tadmin}$ | Tower material admissible strength                |
| $t$               | Blade thickness (ratio)                           |
| $T_{ex}$          | Extreme thrust                                    |
| $T_t$             | Total operational time                            |
| $T_D$             | Total down time                                   |
| $U_0$             | Gear ratio  |
| $U_S$             | Gear stage ratio                                  |
| $U_{SN}$          | Gear sun wheel ratio                              |
| $V_r$             | Rated wind speed                                  |
| $V_t$             | Rotor tip speed                                   |
| $V_d$             | Design wind speed at maximum $C_p$                |
| $V_{ex}$          | Extreme wind speed                                |
| $W_{AYAW}$        | Above yaw mechanism components weight             |
| $W_{BA}$          | Blade aerofoil weight                             |
| $W_{BC}$          | Blade connection weight                           |
| $W_{BPAREA}$      | Blade Nacelle bedplate weight due to area         |
| $W_{BPQ}$         | Blade Nacelle bedplate weight due to torque       |
| $W_{BPT}$         | Blade Nacelle bedplate weight due to thrust       |
| $W_{BPRWT}$       | Blade Nacelle bedplate weight due to rotor weight |
| $W_{BRNS}$        | Bearing system weight                             |
| $W_{BS}$          | Blade spar weight                                 |
| $W_{HS}$          | Hub structural weight                             |
| $W_{NCLAD}$       | Nacelle cladding weight                           |
| $W_{PM}$          | Hub pitch mechanism weight                        |
| $W_{ROT}$         | Rotor weight                                      |
| $W_{TOW}$         | Tower weight                                      |
| $W_{YAW}$         | Yaw mechanism weight                              |

|          |   |
|----------|---|
| $x$      | Time lag for adding R&D                     |
| $\omega$ | Rotational speed                            |
| $Z$      | Number of planet wheels for planetary gears |

## Abbreviations

|        |   |
|--------|---|
| 2FLC   | 2 Factor Learning Curves                                    |
| AEP    | Annual Energy Production                                    |
| BCG    | Bolton Consulting Group                                     |
| BOS    | Balance of Station  |
| BWE    | Bundesverband WindEnergie (Germany Wind Energy Association) |
| BWEA   | British Wind Energy Association                             |
| COE    | Cost of Energy  |
| DD     | Direct Drive  |
| DDSG   | Direct drive Synchronous Generator                          |
| DDPMSG | Direct Drive Permanent Magnetic Synchronous Generator       |
| DEA    | Data Envelopment Analysis                                   |
| DECC   | Department of Energy and Climate Change                     |
| DFIG   | Double Fed Induction Generator                              |
| DOE    | Department of Energy  |
| DR     | Discount Rate   |
| DTI    | Department of Trade and Industry                            |
| EC     | Experience Curves   |
| EWEA   | European Wind Energy Association                            |
| GFRP   | Glass Fibre Reinforced Polymer                              |
| GWEC   | Global Wind Energy Association                              |
| HICP   | Harmonised Index of Consumer Prices                         |
| IEA    | International Energy Agency                                 |
| ICC    | Installed Capital Cost                                      |
| IPCC   | Intergovernmental Panel on Climate Change                   |
| LC     | Learning Curves   |
| LCOE   | Levelised Cost of Energy                                    |
| LD     | Learning-by-doing   |
| LS     | Leaning-by-doing  |
| LR     | Learning Rate   |
| MEC    | Marine Energy Challenge                                     |
| NACA   | National Advisory Committee for Aeronautics                 |
| NGCC   | Natural Gas Combined Cycle                                  |
| NEEDS  | New energy Externalities Developments for Sustainability    |
| NREL   | National Renewable Energy Laboratory                        |
| OECD   | Organisation for Economic Co-operation and Development      |
| O&M    | Operation and Maintenance                                   |
| PF     | Parametric Factor   |
| PMSG   | Permanent Magnetic synchronous Generator                    |
| PR     | Progress Ratio  |
| PV     | Photovoltaics   |
| R&D    | Research and Development                                    |
| SCIG   | Squirrel Cage Induction Generator                           |
| TSR    | Tip Speed Ratio   |
| WEC    | Wave Energy Converter                                       |
| WEM    | Wind Energy market  |
| WECS   | Wind Energy Conversion Systems                              |
| WWEA   | World Wind Energy Association                               |



# 1 Introduction

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## 1.1 Research Problem

A number of early-stage energy supply technologies have the potential to make significant contribution to carbon emissions reduction in future energy mixes. Policy makers and investors require long term forecasts of the role of emerging technologies, but data on their current and future performance is limited. These technologies are less economically competitive than conventional technologies, but there is the potential to reduce costs with innovation. This calls for improved methods for analysing technological progress. Learning curves are often used to assess technological improvements but they have a number of limitations for emerging energy technologies. The focus of this thesis is to find methods of improving their use by introducing complementary methods such as engineering assessments and parametric modelling. This chapter is an introduction to the thesis.

Section 1.2 provides a brief background to the problem. Section 1.3 gives the methodology used for the study. Section 1.4 provides a brief summary on initial work which was carried out in preparation for the thesis and the main case study carried out on onshore wind. The research outcomes are given in Section 1.5. Section 1.6 discusses the limitations of the study. Section 1.7 outlines the thesis structure and Section 1.8 concludes the chapter.

## 1.2 Research Background

The learning curve is a tool for assessing and forecasting cost reduction of a product, achieved through experience from cumulative production. The curves are aggregate in nature, representing overall cost reductions. However, they do not identify the actual factors behind the cost reduction. Understanding the role of factors such as R&D efforts, technological improvements and economies of scale is important in the improved application and interpretation of learning curves. Better distinguishing of

different sources of cost reduction can inform on technical change required to achieve cost reduction targets. Engineering cost assessment methods have been used as an alternative to learning curves to forecast cost reductions, especially for technologies in the early stages of development. Engineering approaches to assessment are generally bottom-up based. The approach involves disaggregating the system into components to analyse individual impact and combining the effects to get the overall cost. The analysis is achieved either qualitatively or quantitatively with more detail and calculations for the components.

Learning curves and engineering assessments are two approaches with similar overall goals of cost assessments, but distinctive strengths and weaknesses. In their aggregate nature, learning curves do not offer detailed technology information required for short term technological improvements. Engineering methods involve more detailed technology specific approaches, but on their own, they do not provide long term forecasts required for policy strategies. Neither method can therefore fully represent progress of emerging energy technologies. By bringing them together, this thesis attempts to address limitations of learning curves, while at the same time taking advantage of their observed benefits. The bringing together of two established but distinctive approaches will be a challenge which will be tackled through research and networking with other contemporary work. A third approach, parametric modelling, is an engineering based method that has been used for the analysis of technologies and products in their early stages of development, and might be useful in the integration of the two methods.

### **1.3 Research Methodology**

The research will attempt to develop methods based on cost drivers or cost centres that have an impact on cost of electricity. Cost assessment models will be developed for the more established emerging electricity supply technology, onshore wind energy, and then the knowledge of developing such models can be adapted for offshore wind and possibly marine energy cost assessments.

A literature survey on learning curves, engineering assessments, parametric modelling and innovation studies was carried out at the beginning of the study. This

highlighted the recent growth in applying learning curves to the energy sector, and also its limitations for emerging energy technologies. It also identified relevant engineering based assessments that have potential for use in the study.

An early stage case study was carried out to review learning effects and learning curves for wave energy technologies from 1970s to the 1990s in the UK (Mukora, Mueller et al., 2008). Although learning curves were not explicitly applied for this period, and there are limits to their use for this early stage technology, the case study suggested that awareness of the tool could have contributed to improved progress of the technology. It was also suggested that knowledge gained in earlier research might have continuing impact on the development of wave energy in the future, especially if this is made more accessible and the stock of knowledge is utilized. The study was a useful starting point for the research, and challenges in developing learning curves for emerging technologies were noted from this. It also informed the choice of the technology for developing the model. The results of the study were presented at a conference (Mukora, Mueller et al., 2008).

### **Wind turbine case study**

Engineering assessments, parametric modelling and learning curve methods will be applied to onshore wind energy. The main focus for the engineering assessments will be the disaggregation of the turbine into individual components or subsystems to estimate cost and identify possible sources of cost reduction. Secondly, a parametric based model will be developed for predicting cost changes due to technological improvements. Finally, the results of the first two stages and information on onshore technology development trends will be used to find means of improving learning curves analysis. Ultimately, the models could then be upgraded by including parameters that take into account other non-technical parameters, such as policy and market factors. In the early stages of the study, the approaches proposed for learning curves improvements in this thesis were discussed in a paper that was published, a copy can be found in the appendices (Mukora, Mueller et al., 2009).

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## **1.4 Limitations**

The extent to which this study is carried out will depend on data availability. Where market based data is limited, modelled data will be used and will be validated with any relevant data that can be found in the literature. The study will be based on a quantitative analysis on onshore wind, a more established technology with relatively more data available. Due to time and resource constraints, the application of the developed assessment methods to offshore wind will be limited to qualitative analysis and it is suggested that further studies from this would include upgrading the proposed quantitative methods for offshore turbines furthermore for wave and tidal technologies.

## **1.5 Research Outcomes**

The research was intended to result in improved cost assessment models for emerging energy technologies through the integration of the learning curve methods, engineering assessment methods and parametric modelling. The major outcome however, was the knowledge and experience of developing such a model. At the beginning of the study it was anticipated that the development of a plausible curve that can be defended would result in improved understanding and interpretation of the shape of the learning curve and the factors that shape it.

The documented evidence for the development of the model is meant for research in emerging energy technology progress forecasting. This kind of integrated analysis promises to better inform the shape of the learning curve for emerging energy technologies, by going beyond only predicting future costs based on cumulative production, but also other factors such as the innovation which can be manipulated to accelerate learning. These can be used to improve data based methods for energy system models that use learning curves. It is a step towards complete representation of technological progress of emerging energy technologies taking into account changes that are not directly related to experience, such as design changes, manufacturing developments, market and policy influences. It was anticipated that the process of developing such a model will assist in the elimination of some



identified uncertainties in the use of learning curves and also enable the modelling of possible discontinuities and jumps in the learning curve.

Through the onshore case study, the study managed to achieve the following:

1. Step by step and upgradeable detailed assessment of a 2 MW commercial turbine based on engineering design principles for the cost of energy components for the COE.
2. The use of parametric modelling to account for impact of change such as upscaling on cost. The thesis made a new contribution in developing new scaling exponents used in parametric models and the derivation of wind turbine component parametric factors that simplify the modification of the reference turbine to account for changes in the turbine size and the change of the standard DFIG turbine to direct drive drivetrain.
3. Integration of data from engineering assessments and learning curve analysis and the assessment of such data and the development of a method for disassembling and reassembling the learning curve through the integration of engineering assessment methods to include the impact of short to medium term changes such as upscaling of wind turbines and drivetrain changes.
4. Analysis of the use of similar methods to take into account the impact of other cost changes to learning curve analysis for onshore wind energy and other emerging energy technologies thus resulting in improved cost assessment of early stage energy technologies.

## **1.6 Thesis Structure**

The thesis is structured into nine chapters. Chapter 2 is a literature survey on learning curves, engineering assessment and parametric modelling. Chapter 3 looks at methodological issues associated with the application and development of learning curves in their simple form or improved through the use of other methods as given in literature. The conclusion to Chapter 3 highlights the need to develop specific technology based methods and onshore wind is chosen for this purpose. Chapter 4 introduces onshore wind energy giving an overview of the wind turbine components and onshore wind energy historical and current technological trends. Chapter 5 gives

the initial engineering assessment of a chosen reference turbine based on turbine component weight estimations. Chapter 6 provides the cost results for the turbine and other wind energy costs. Chapter 7 gives parametric modelling based methods used for modifying reference turbine costs to account for changes in the technology brought about by innovation. Chapter 8 provides methods of combining the results of the engineering assessments and parametric modelling with learning curves for wind energy technology. Finally, Chapter 9 discusses the results for onshore wind and the application to offshore wind and other technology and it finally concludes the study.

## **1.7 Conclusion**

The integration of engineering methods and parametric modelling into learning curve analysis involves bringing together potentially complementary approaches that have been used for different purposes so as to build a more complete representation of learning effects for emerging energy technologies – and thereby provide improved data for energy systems modelling and policy on alternative energy. Existing studies illustrate the possible synergies to be gained from combining these different approaches in addressing the same goal of cost reduction exist, but work involving their integration is still limited. Fully representing and forecasting technical change for early stage technologies is a formidable challenge. However, it is anticipated that the generic modelling approaches resulting from this study can offer steps towards more complete representations of the cost reduction drivers for these technologies within learning curves. The next chapter provides a better understanding of learning curves and the other assessment methods through a literature survey.

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## 2 Literature Review

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### 2.1 Introduction

The transition to a sustainable energy system requires policies and strategies that encourage the development and deployment of alternative sources of energy supply. A number of early-stage low carbon energy supply technologies have the potential to make a significant contribution to carbon emissions reduction in future energy mixes. These emerging technologies are technically feasible, but fall short economically in comparison with conventional sources. However, they have the potential to reduce costs if deployed but growth will depend on further development through innovation and experience. The role of emerging energy supply technologies in future energy mixes, in the context of global energy challenges and current turbulent economic climate, is in part reliant on the development of improved methods of cost assessment and forecasting technical change.

This chapter reviews literature on quantitative assessment methods for emerging energy technologies, in particular, the role of learning curves: a well known tool for measuring the impact of technical change and policy measures on the cost reduction and implementation of new technologies. The use of engineering assessment and parametric modelling methods for emerging energy technologies are also discussed.

Section 2.2 gives a brief introduction to emerging energy supply technologies and their role in the context of carbon reduction within the energy supply industry. Section 2.3 provides a literature review of learning curves discussing their use and limitations for emerging energy technologies. Section 2.4 introduces engineering assessment methods with an emphasis on the costing of new technologies and a brief discussion on their limitations when applied to emerging energy technologies. Parametric modelling is briefly introduced in section 2.5 followed by a discussion of the methods in section 2.6 and section 2.7 concludes the chapter.

## 2.2 Emerging Energy Supply Technologies

Globally, the energy sector is under pressure to find sustainable solutions to the challenges it faces (Jamieson, 2011). These challenges, such as, ensuring supplies in the wake of growing demand in developing countries and emerging economies, reduction in conventional sources of fuel, instability in some of the major oil rich countries and the global financial crisis. The recently extended Kyoto Protocol (Harrabin, 2012), on greenhouse gas reductions gave a new sense of urgency to energy technology policy for countries and regions after its adoption in 1997 (IEA, 2000).

The long term solutions to environmental issues call for technical changes in the energy sector and policy to support innovation and deployment of low carbon technologies is key to mitigation of climate change (DTI, 2007). New low carbon electricity supply technologies such as onshore and offshore wind; wave and tidal, solar photovoltaic (PV) and bio-energy are emerging technologies that could provide this technical change, but they are typically capital intensive and costly compared to conventional sources (oil, coal and gas). The current cost disadvantage of these technologies has the potential to reduce their relevance in climate policy strategies (Albrecht, 2007). In spite of cost reduction potentials of deployed early stage technologies, relevant cost assessment methods are an inherent element in climate change policy analysis guaranteeing the role of the new energy technologies in the future energy mix.

Limited historical data is available for emerging energy technologies due to the lack of operational experience. Consequently, cost assessment models applied to mature technologies are less relevant to the new technologies. There is therefore, a need to find ways of developing current methods for technological assessment to suit emerging energy technologies. A better understanding of factors that shape cost reduction and the way these can be shaped by policy is key to achieving competitiveness and reaching parity with conventional sources. Factors that shape cost reduction are better expressed analytically as learning effects, and quantitatively

as learning rates which are represented on learning curves (McDonald and Schrattenholzer, 2001; Junginger, Van Sark et al., 2010).

## 2.3 Learning Curves

Learning curves or experience curves give an indication of the potential for cost reduction of new technologies as experience is gained (IEA, 2000; Junginger, 2010; Jamieson, 2011). They describe the cost reduction of a technology as a function of cumulative experience in terms of units sold or units produced or installed, and can provide an indication of the investment required for the cost of new technology to breakeven with conventional technology (Alberth, 2008).

In the literature, the terms “learning curves” and “experience curves” have been used interchangeably (Clarke, Weyant et al., 2006; Papineau, 2006; Sark, 2008; van der Zwaan and Clas-Otto, 2011; Yeh and Rubin, 2012). However, some researchers argue that the original learning curve concept focussed on the analysis of the cost of individual inputs to the factory process such as labour cost, whereas, experience curves focus on the total costs relating to the cumulative quantity (IEA, 2000; Papineau, 2006). For this reason, some of the literature has resorted to using the term “experience curves” for the cost of energy technology. (Rubin, Yeh et al., 2007; Alberth, 2008; Neij, 2008; Nemet, 2009; Weiss, Junginger et al., 2010). Throughout this thesis the term “learning curves” is used to refer to all costs related to learning effects due to operational deployment (Jamasb and Kohler, 2007; Solderholm and Sundqvist, 2007; Schoots, Ferioli et al., 2008; Mukora, Mueller et al., 2009), rather than the term “experience curves”.

The learning mechanism resulting from cumulative experience is known as *learning-by-doing*, although cost reductions with deployment may also reflect the impact of other sources. A single parameter, the learning rate (LR), quantifies the relationship between experience and cost as the percentage of cost reduction achieved with each doubling of production or installation (Jamasb and Kohler, 2007; Solderholm and Sundqvist, 2007; Jeffrey, 2008; Neij, 2008). Alternatively, progress ratio (PR) is used to quantify learning effects and it is the corresponding percentage to which cost is reduced with each doubling of cumulative production (Junginger, Faaij et al.,

2005; Alberth, 2008; Sark, 2008; Junginger, Van Sark et al., 2010). The learning rate is mainly used for this study and is related to the progress ratio by the following relationship: (100% - Progress Ratio) (IEA, 2000).

Learning curves are constructed using mathematical relationships which were derived from historical observations. The unit cost  $C_t$  of a product or technology at any cumulative production  $q_t$  can be estimated by the following relationship:

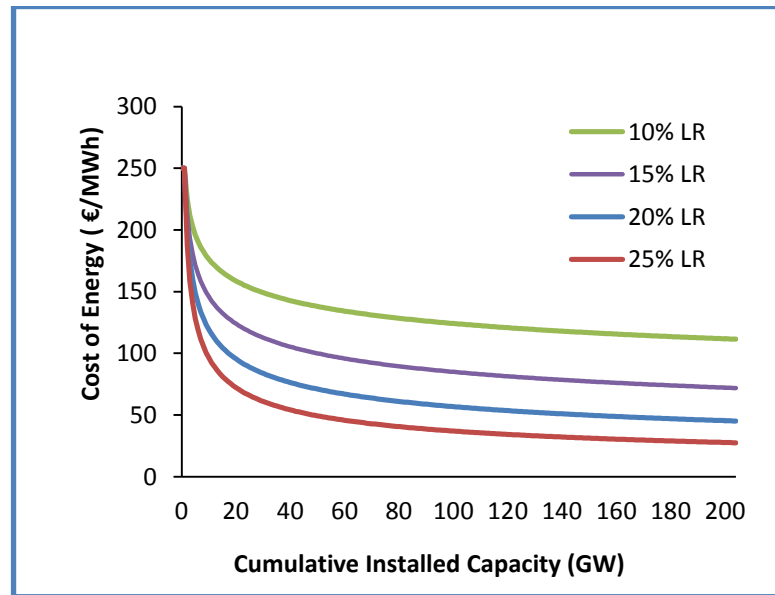
$$C_t = C_0 q_t^{-\alpha} \quad 2.1$$

Where  $C_0$  is the cost of the first unit, and  $\alpha$  is experience index used to estimate the learning rate ( $LR$ ) or the progress ratio ( $PR$ ) as:

$$LR = 1 - 2^{-\alpha} \quad 2.2$$

$$PR = 2^{-\alpha} \quad 2.3$$

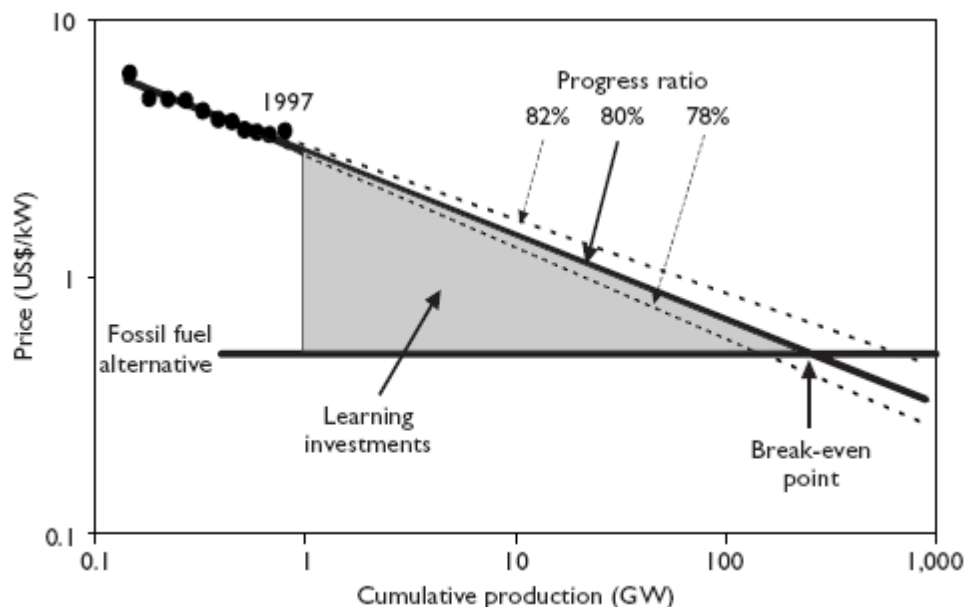
Typical learning curves for different learning rates are illustrated in Figure 2.1.



**Figure 2.1** Cost of Energy Learning curves

The figure is a representation of the cost reduction trends for a technology with a unit cost unit of 250 €/MWh for the first GW. The learning rate of any product or

technology is constant for any part of the simple learning curve and a higher rate implies cost reduction taking place at a higher rate. The learning curve can be plotted on a log-log scale to make it easier to analyse. The resulting curve becomes a straight line as shown in Figure 2.2.



**Figure 2.2** Learning curves for solar photovoltaics (PV) installation costs plotted on a log-log scale (IEA, 2000)

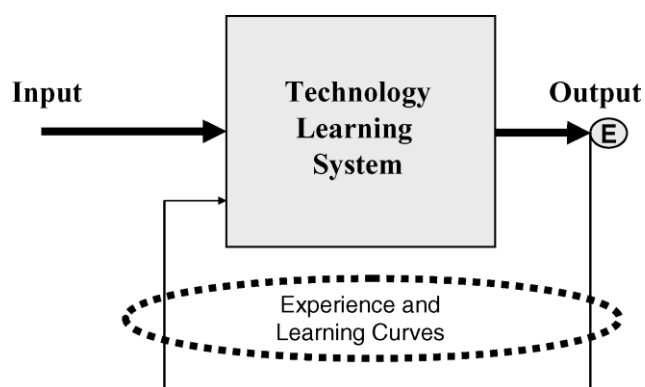
Figure 2.2 also shows a representation of another important assessment parameter, *learning investment*: the suggested investment on developing a product or service that can reduce its cost to the level of established products or services. It is generally assumed that a technology follows a path on the same learning curve towards maturity as capacity increases. The constant learning rate on a learning curve in its general simple form implies that the technology remains the same as cumulative production increases with no considerable innovation and technological developments.

Learning curve approaches allow comparisons of different technologies at different stages of development. A high learning rate reflects a high rate of cost reduction (either realised or potential) provided that learning investments are made available, and that these have the anticipated impact on cost and performance. As technologies

mature, more and more installed capacity is needed to double cumulative capacity. As a result, the impact of each unit of additional capacity on unit cost is reduced (Anderson and Winne, 2003). Learning rates also vary between different technologies according to their scope for cost reduction or performance improvements.

Learning curves assist in the identification of those technologies that are likely to achieve the greatest progress in terms of cost reduction during the foreseeable future with adequate investments (McDonald and Schrattenholzer, 2001; Jamasb, Nuttall et al., 2006; Junginger, Van Sark et al., 2010). They help illuminate the dramatic cost reduction in early development stages of a technology innovation. (Grubb, Kohler et al., 2002) and can connect future cost developments to current investments in new technology (Soderholm and Sundqvist, 2007). Although learning curves show investments necessary to make a technology competitive, on their own they do not forecast the time when it will break even with conventional technology, but the cumulative installed capacity at which this happens.

In some studies, learning effects have been described as a black box, referring to observed cost reductions brought about by experience resulting from cumulative production (Ferioli, Schoots et al., 2009; Lapre, 2009). From this point of view, the basic learning model can be represented as shown in Figure 2.3 with inputs and outputs to the environment (E) that can be observed, but does not make any hypothesis about the processes going on inside the learning system (IEA, 2000; Wene, 2008).



**Figure 2.3** Black box learning system (IEA, 2000; Wene, 2008)



*Learning-by-doing* is generally the learning effect that describes cost reduction due to experience and is quantitatively estimated using learning rates from simple learning curves. Understanding the distinctive role of different causal factors – such as R&D efforts, diffusion and economies of scale (Jamasp and Kohler, 2007) – is important in the improved application and interpretation of learning curves.

In addition to learning-by-doing, Kamp (2004) suggested three other learning curve mechanisms: *learning-by-using*, *learning-by-interacting* and *learning-by-searching* (also referred to as: *learning-by-research*) (Kamp, Smits et al., 2004). Other possible learning effects have been suggested in literature. For example, according to Harmon (2000), cost reduction in PV modules was attributed to technology innovation, manufacturing improvements and economies of scale. Neij (1997) and Yeh et al. (2007) suggest changes in input price as another source of cost reduction, in addition to product and process change. Coloumb and Neuhoff (2006) emphasised the need for consideration of significant changes of physical attributes of a technology when assessing the impact of learning-by-doing.

It can therefore be said that although cost reduction has been estimated using learning curves based on experience attributed to learning by doing, other underlying factors have an impact on cost reduction. Distinguishing these different sources of cost reduction can help inform policy measures for achieving cost reduction targets and innovation pathways. Whether these cost reduction effects are implicitly included in the aggregate learning rate or are missed, the simple learning curve models do not show any indication of such. Considerable efforts however, have been made of attempting to isolate some of the perceived sources of cost reduction. In particular, the role of R&D efforts in bringing about technological change in emerging energy technologies has been explored (Neij L, Andersen P.G et al., 2003; Barreto and Kypreos, 2004; Miketa and Schrattenholzer, 2004; Jamasp and Kohler, 2007; Alberth, 2008). (Klaassen, Miketa et al., 2005; Alberth, 2008).

### **2.3.1 Use of Learning Curves for Energy Technologies**

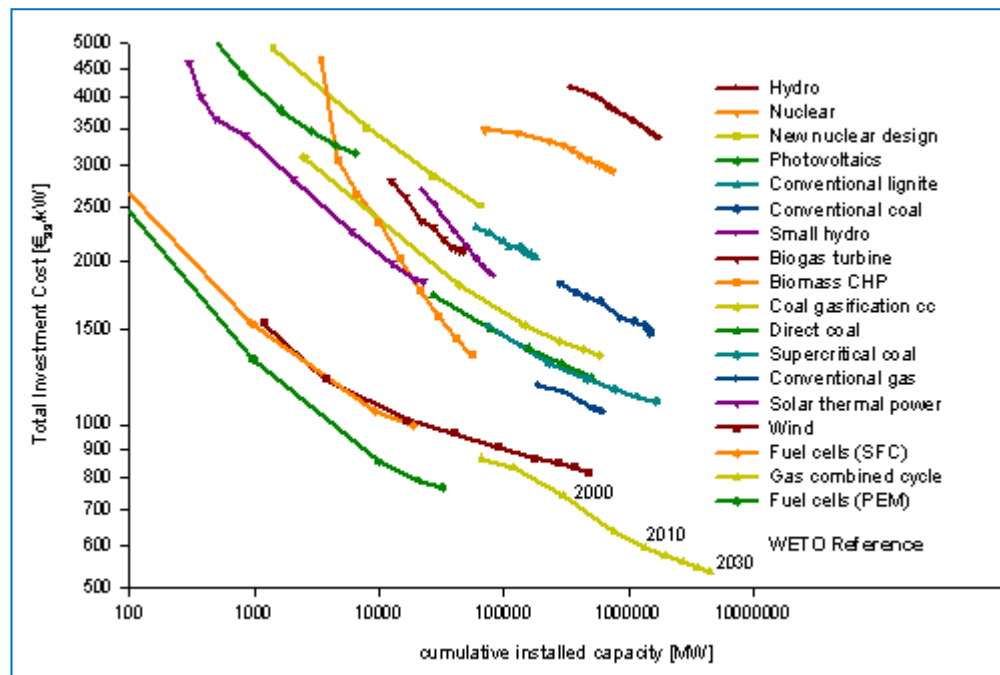
The learning curve concept dates back to 1936 when it was used by Wright (1936) who estimated the relationship between labour hours and cumulative airplane

production. In the 1960s it was adapted by BCG Consulting group from the learning by doing literature in economics (Neij L, Andersen P.G et al., 2003). Its popularity in production and planning and strategic management reached a peak in the mid 1970s and the concept lost favour when forecasts of long term predicted cost reductions were not achieved (Lieberman, 1987)

Since the 1990s learning curves have found renewed interest in contemporary research in energy systems for the purposes of technology and policy analysis as governments search for ways to address climate change (Jamاسب, 2006). In particular, there has been considerable interest in energy systems models where the generation of meaningful and policy relevant results have become dependent on reliable estimates of learning rates. (Soderholm and Sundqvist, 2007).

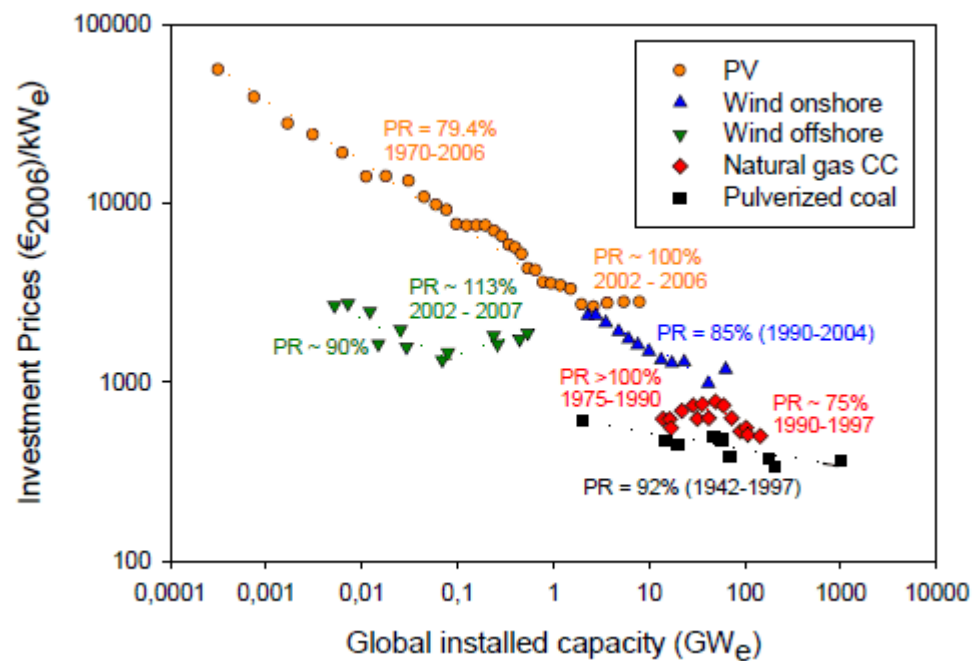
In the past, technical change was seen as just exogenous to the economy, but the new paradigm in energy systems modelling views technical change as also endogenous to the economy (Jamاسب, 2006; Jamieson, 2011; Yeh and Rubin, 2012). Quantitative modelling of experience has become a common method of representing endogenous technical change in energy forecasting models and for generating reliable data estimates for model inputs (Soderholm and Sundqvist, 2007; Yeh, Rubin et al., 2007). Berglund and Soderholm (2006) gave an overview and critical analysis of literature on incorporating induced technical change in energy system models (Berglund and Soderholm, 2006).

The simplicity and apparent predictive power of learning curves have led to their application in everything from manufacturing, chemical processing, textile production to nuclear plant production (Papineau, 2006). The growing interest in the application of learning effects and learning curves to emerging energy technologies has been researched and studied considerably. (McDonald and Schrattenholzer, 2001; Neij, 2008; Junginger, Van Sark et al., 2010; Yu, Van Sark et al., 2011). Figure 2.4 presents learning curves the majority of energy supply technologies including conventional sources.



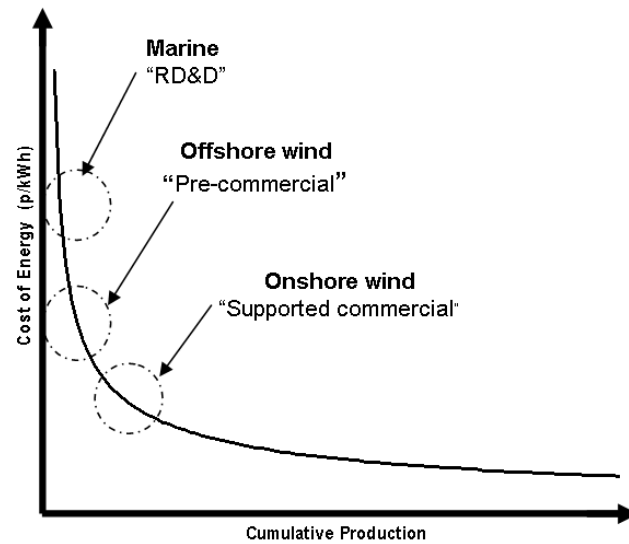
**Figure 2.4 Learning curves for power generation technologies based on historic data and projection up to 2030 (Kouvariatakis, 2000).**

Wind energy technology has been covered in a wide range of learning curves literature (Neij L, Andersen P.G et al., 2003; Miketa and Schrattenholzer, 2004; Coulomb and Neuhoff, 2006; Kobos, Erickson et al., 2006), as well as solar photovoltaic (PV) (van der Zwaan and Rabl, 2003; Albrecht, 2007; Yu, Van Sark et al., 2011). Other technologies studied include bioenergy, hydrogen and solar thermal (Krawiec, 1991; Neuhoff, 2005; Junginger, de Visser et al., 2006; Schoots, Ferioli et al., 2008). The technologies have different learning rates depending on level of deployment and maturity. Figure 2.5 shows historical learning rates for solar pv, onshore wind, offshore wind, natural gas combined cycle plants and pulverised coal power stations giving indications of average learning rates over periods of time.



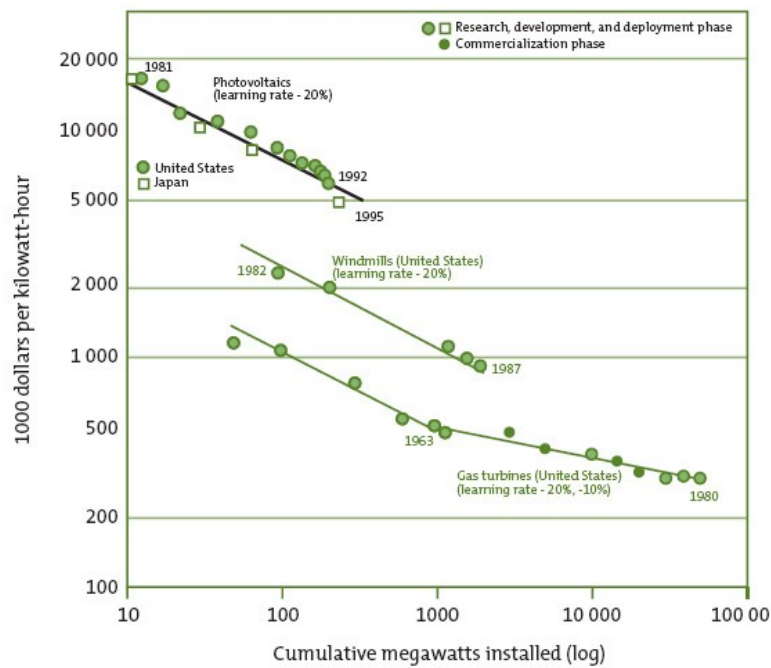
**Figure 2.5 Learning curves of major energy technologies (Green-X, 2012)**

Attempts have also been made to explore the application of the learning curves concept for assessing possible cost reduction potential of the relatively new marine energy technologies-offshore wind, wave and tidal energy (Junginger, Faaij et al., 2004; Mukora, Mueller et al., 2008; Greenacre, Gross et al., 2010; Junginger, Van Sark et al., 2010). Figure 2.6 shows relative position of emerging energy technologies plotted on a hypothetical learning curve. In reality, as stated earlier, technologies have different learning rates implying different curves.



**Figure 2.6** Relative positions of mechanical emerging energy technologies plotted on the same learning curve.

Newer technologies lie at the top of the curve relative to the established technologies which lie in the lower flat region. This means that new technologies learn faster from market experience than old technologies with the same learning rates (IEA, 2000; Junginger, Lako et al., 2008). The same absolute increase in cumulative production will have a more dramatic effect at the beginning of a technology's deployment than it will later on as it approaches maturity. Figure 2.7 illustrates that gas turbines in the commercialisation stage lie in the lower regions of the learning curve plots compared to wind energy and solar pv according to level of deployment and installed capacity.



**Figure 2.7** Learning Curves Experience curves for photovoltaics, windmills, and gas turbines in Japan and the United States (Ahuja, D. and T. Tatsutani, 2009)

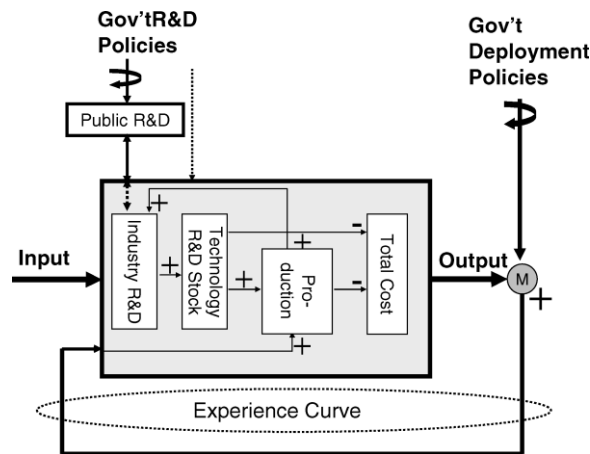
### 2.3.2 Role of R&D and Learning Curves

The effect of R&D on technology cost reduction has been described as being analogous to experience, in that it brings about dynamic economies or downward shifts in the cost curve and R&D effects can also interact with the learning curve effects to increase the pace of dynamic savings (Papineau, 2006). R&D and installed capacity are therefore important sources of cost reduction in new energy technologies.

Investments in R&D can help achieve cost reductions throughout all stages of a product's life cycle (Alberth, 2008). In general, progress in emerging technologies during the early stages of development is likely to be achieved primarily through R&D because installed capacity and market experience remain limited (Papineau, 2006). In some studies, the analysis of learning rates has been extended to the so-called 'two-factor' learning curves (2FLC) by explicitly distinguishing between discrete learning effects, such as learning-by-researching, and learning-by-doing. For learning-by-research, R&D may be assumed to enhance the 'knowledge base'

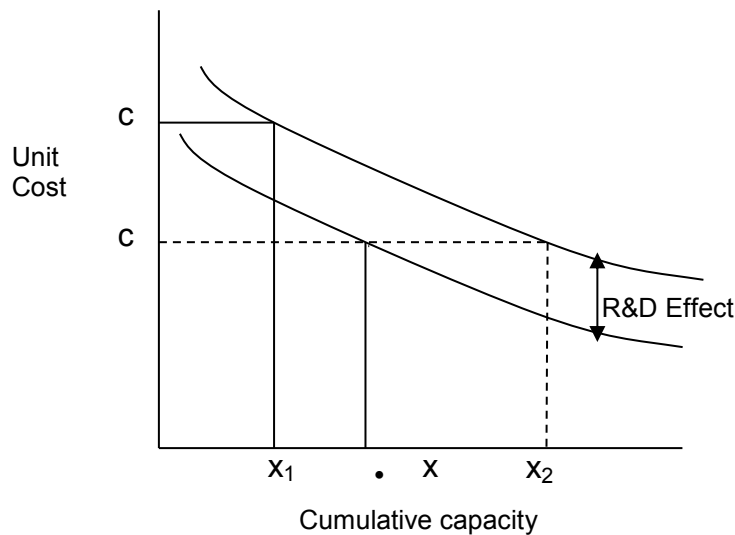
which drives forward technical progress (Jamasp, 2006). Two factor learning curves (2FLCs) explicitly incorporate R&D factors so as to avoid overestimation of the learning-by-doing effect.

Wene (2008) suggested the opening up of the learning system black box by isolating the role of R&D efforts. He proposed a system where government R&D efforts influence the learning system whose output together with government deployment policies have an impact on the market (M) as illustrated in Figure 2.8 (Wene, 2008).



**Figure 2.8** Adapted learning system isolating R&D efforts. Source (Wene, 2008)

Jamasp (2006) found that though R&D is not the only source of technical change, it is present in all stages and there is no development stage where learning by doing alone is the dominant driver of technological change. He proposed an improvement of the learning curve through representation of R&D effects as shown in Figure 2.9.



**Figure 2.9 Representation of the role of R&D in learning curves (Jamashb, 2006)**

It can be seen from Figure 2.9 that R&D efforts have the possible effect of shifting the learning curve to a curve with a higher learning rate. It is as yet to be established whether 2FLCs will provide a sound aggregate model (Barreto and Kypreos, 2004; Klaassen, Miketa et al., 2005; Yeh and Rubin, 2012). Research efforts into the use of 2FLC are still limited and there are challenges associated with quantifying R&D efforts, whether public or private, and sourcing relevant R&D data. The possibility of both R&D investments and cumulative capacity responding to the same cost drivers and directly influencing each other can complicate 2 factor learning curves.

### 2.3.3 Uncertainties in the use of Learning Curves

The learning curve is a valuable tool for assessing and forecasting technological change but its use especially in energy technologies is associated with a lot of uncertainties and limitations (Jamashb and Kohler, 2007; Yeh, Rubin et al., 2007). Some literature suggests that the learning curve is not an established theory but a correlation phenomenon which has been observed for several years (Neij, 1997). The curves are simply empirically observed relations, and there is no natural law causing cost to decline with cumulative production (Junginger, de Visser et al., 2006). The learning curve method is therefore a heuristic measure without solid theoretical basis (Alberth, 2008).



Limitations to the application of learning curves have been discussed considerably in the literature (Yeh, Rubin et al., 2007; Alberth, 2008; Ferioli, Schoots et al., 2009; Yeh and Rubin, 2012). Andersen (2003) states that if the nature of the technology in question and the industry structure around it is not correctly understood, development and use of learning curves will involve many errors (Andersen, 2003) and can end up giving misleading insights (Day and Montgomery, 1983; Yeh and Rubin, 2012). The main concern in the learning curve is that in its original aggregate form, it does not address all factors that affect cost reduction. The main uncertainties and limitations are discussed below.

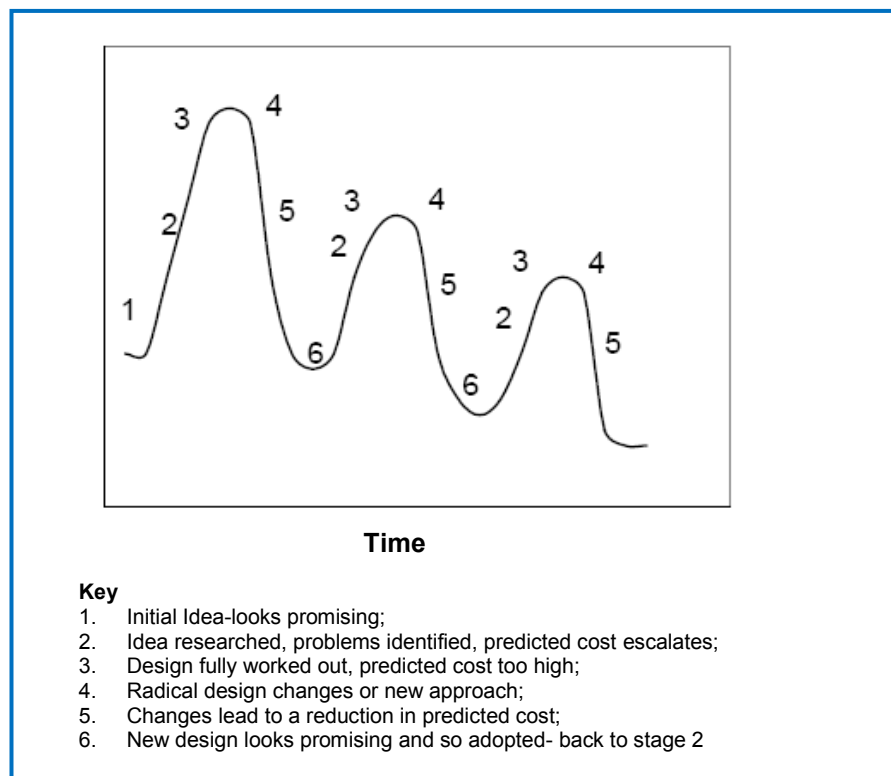
### *1. The Aggregate Nature of the Learning Curve*

Learning curves typically represent how costs have reduced over time, but provide no explanation of the reasons behind the cost reduction (Nemet, 2006). They do not allow direct identification of logical sources of cost reduction. Efficiency improvements are often implicitly embedded in unit cost data, but this is not always the case (Yeh, Rubin et al., 2007). Interactions of cost and performance need to be better addressed (Junginger, de Visser et al., 2006). The 2FLC method reduces the likelihood of overestimation of learning-by-doing effect, but assessing and quantifying R&D effects is difficult because of lack of publicly available data (Alberth, 2008) and the use is also associated with uncertainties. This approach does not isolate other sources of cost reduction besides R&D effects. Learning curves provide no means of modelling short term discontinuities such as those that might result from technological development and innovation or any other disruptions. Aggregating industry learning curves might also carry errors because it does not take into account the learning taking place in other sectors, often referred to as spillover effects (Alberth, 2008).

### *2. Data availability and early cost estimates*

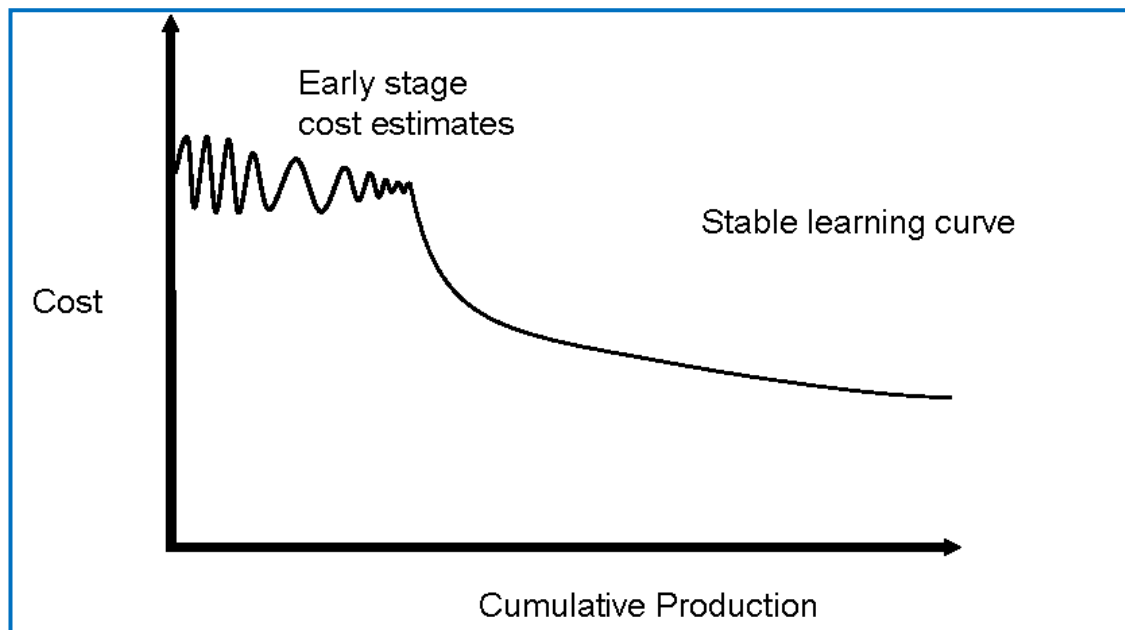
The use of learning curves to assess the effect of combined policy measures in terms of cost reduction is only achievable with relevant learning curves based on good and reliable data (Neij L, Andersen P.G et al., 2003). This is a challenge for emerging technologies as there is normally a lack of detailed data for deriving historically

based empirical experience (Junginger, de Visser et al., 2006; Greenacre, Gross et al., 2010). Learning rates for analogous technologies with historic data are sometimes used, but the accuracy of such is always arguable and this introduces new uncertainties. Cost estimates of new technologies may vary widely especially in the early stages of deployment before they stabilise. Figure 2.10 illustrates an example of a typical cost trend for a technology in the early stages of development.



**Figure 2.10 Characteristic variation in predicted cost of technology over time (Thorpe, 1999)**

Figure 2.11 shows a more likely learning curve of an emerging technology which has dynamic cost estimates in the early stages after deployment and then stabilises after the technology becomes more established in the market. This phenomenon has been addressed in some studies, but there are few empirical studies that document such trends for energy technologies (Yeh, Rubin et al., 2007).



**Figure 2.11 Early Stage Cost Forecasting**

Data and methods for developing such learning curve models are limited. It is more appropriate to choose the starting point at later stage of deployment than the very first unit of production (Ferioli, Schoots et al., 2009).

### 3. Cost Increases (*negative learning*)

It is anticipated that cost will come down, but in reality, cases of cost increases can be observed. This results in so-called *negative learning effects* and negative learning rates (Grubler, 2010). In early stage technologies, this is mainly due to the instability in cost in the initial stages of development as shown in Figure 2.10. In addition, cost increases can also be observed when a technology is more established and on the stable part of the learning curve. In the same way experience results in the accumulation knowledge of doing things over time, the knowledge can depreciate and be forgotten resulting in cost increases (Jain, 2012; Yeh and Rubin, 2012). Grubler (2010) used a case study of the French nuclear reactors to discuss the contrast that can exist between forecasts and reality. The case demonstrated the limits of the learning curve as the cost of nuclear reactors increased rather than declined, exhibiting a negative learning rate. The increases varied across countries and this raises questions on the reliability of global learning curves (Grubler, 2010).

#### 4. *Learning rate estimates*

A single learning rate for a technology is often assumed, but important differences in learning effects may be expected at different stages of development (Grubler, Nakicenovic et al., 1999; Mukora, Mueller et al., 2009). Learning rates may also be expected to vary significantly over time, and there is a need to allow for actual or potential discontinuities, step-changes or radical breakthroughs.

In brief, the main limitations in the use of learning curves arise due to their aggregate nature, their concern with outcome rather than process, and the need for reliable input data over sufficiently long time periods. These difficulties may be more pronounced for emerging energy technologies for which data and experience is inevitably limited. There is therefore a need to improve current methods of constructing and interpreting learning curves to address these uncertainties, especially for emerging low carbon energy supply technologies. Learning curves are based on a model of innovation which emphasises deployment and continuity of policy support. The framework of innovation underpinning this tool accentuates the stimulation of incremental deployment and continuity (Mukora, Mueller et al., 2009). Although relatively well established and supported by evidence across a number of sectors (Papineau, 2006), learning curves are essentially representations of innovation *outcomes*, and are only weakly based in theories of innovation *processes*. Thus said, learning curves can be seen as emphasising learning-by-doing (through deployment) and the need for continuity of early support mechanisms.(IEA, 2000) They model overall costs or price and, in their aggregated and outcome-oriented nature, do not attempt to identify the causal factors behind the cost reduction (Nemet, 2006).

In summary, learning curves were developed for technologies that differ from emerging energy technologies. Emerging energy technologies are still undergoing innovation through product design and process changes achieved through engineering efforts. Integration of learning curves with engineering design techniques and innovation theory for technological change can assist in adapting the

learning curve theory for these technologies. In most literature, innovation systems are not viewed technically but in the economic sense. Simple learning curves are based on a paradigm that emphasises deployment and continuity with no significant technological changes. The need for innovation in emerging energy technologies necessitates further development of learning curve methods for emerging energy technology which take into account technological change as experience is gained.

## **2.4 Engineering Assessments**

A number of engineering assessment methods are available which make use of relationships between engineering design and performance (Harrison, Hau et al., 2000; Clifton, 2004; Karjalainen, Bescherer et al., 2007; Roy, 2007; Wrobel and Laudanski, 2008). Engineering approaches to assessment disaggregate the system into components for detailed analysis. They provide detailed project costs and limited long term forecasts required for policy strategies and investment decisions.

Engineering approaches to assessment of future cost and performance of technologies are generally bottom-up, in that the technology system is disaggregated into subsystems and components to analyse quantitatively individual contribution to, for example, total mass or cost (Roy, 2003). The individual effects are recombined for the technology, using weighting factors depending on the assumed contribution of the effect. This analysis may be qualitative or quantitative with varying levels of detail (Neij, 2008). Qualitative analysis is common for early stage technologies where resources are limited or to get a first order estimate. The use of expert judgment is one such approach employed in engineering assessments through methods such as structured interviews (Junginger, Faaij et al., 2004). Experts can also make calculations for future predictions based on their engineering experience (Neij, 2008). In some instances, assessment of new technologies is accomplished by categorising the technology and forecasting its technological progress by benchmarking similar technologies whose progress is known (Chapman and Gross, 2001; Jamasb, 2006). Engineering cost assessment therefore has great importance even at early stages of product life where cost reduction potential can be analysed leading to the exploration of the most economic design concepts.

### 2.4.1 Cost Estimation of New Technologies

It is a challenge deriving cost in early stages. The design may still be at the concept stage providing little concrete data against which a cost can be generated. Structured methodologies to perform cost estimates of technologies at the concept stage are limited. According to Bole, cost factors are always changing and direct evaluation is only possible when production design is finalized (Bole, 2006). However, product costing should start before the structured product development phase to ensure cost is managed at all phases of a product life (Roy, Colmer et al., 2005).

New energy technologies are commonly categorised in a spectrum ranging from emerging to mature technologies (Chapman and Gross, 2001; Jamasb, 2006). Another way of categorisation (employed, for example, by the automotive industry) is to define technologies as either *new to mankind*, *new to industry* or *new to organization* (Roy, Colmer et al., 2005). The new product or technology can be further analysed or broken down for:

1. New content type for company or organisation
2. New with similar attributes to a specific design
3. Modified- redesigned from an existing stated design
4. Carry over: exactly the same as existing design (Roy, Colmer et al., 2005).

Once the concept is broken down, respective components or subsystems are categorised and entered into appropriate analysis models. The models developed for the components will be dependent on the category they fall into. Models for components which have common elements with existing ones will be easily derived from the models of those existing designs. On the other hand, alternative concepts with purely new content will require new models.

There are several techniques used for developing cost models applicable at different stages of a product or technology (Wrobel and Laudanski, 2008). The techniques are dependent on the type of costing. Costing in engineering has been classified in various ways in the literature (Roy, Colmer et al., 2005; Roy, 2007; Wrobel and Laudanski, 2008). The most common way is to classify them as traditional and

detailed methods. Traditional approaches are usually done in the early stages based on the experience of the designer. Detailed costing is based on a number of operations based on all the cost drivers. It is necessary to have an in-depth understanding of the technology and the manufacturing processes to produce it. Detailed analysis is achievable when a product is well defined and understood. Traditional costing can be done by analogy based on a similar technology which is more established and can be assessed using existing design methods. (Roy, 2003; Wrobel and Laudanski, 2008). This approach might prove essential for emerging technologies where data and cost driver information for detailed cost and design analysis is limited but similar to existing technologies.

### **2.4.2 Limitations of Engineering Assessments**

Engineering assessments, though useful in providing further analysis into cost drivers and assessment of cost reduction potential, also have limitations with respect to their application to emerging energy technologies.

- i. Engineering assessments do not provide long term cost forecasts, the interest of investors, policy makers and energy system modellers
- ii. A number of approaches to cost assessments exist and may result in different estimates and different metrics of assessment.
- iii. Detailed analysis is resource intensive in terms of time and modelling effort
- iv. Engineering assessments are too project specific or company specific, being dependent on the company policies and approaches to design and manufacture as well as deployment methods for energy technologies. The methods may have limitations in their use for global analysis.

The limitations in the use of engineering assessments are mainly associated with their detailed nature which is resource consuming and not ideal for long term forecasting and general analysis of historical trends. The bottom-up approaches are at an extreme end of the aggregated top-down learning curves approach. The major strengths of each of these two analysis methods are the weaknesses of the other, thus making them complementary. However, the use of these two methods together, which are in extreme positions, might pose some challenges. Parametric modelling,

another intermediate cost engineering based approach which might be useful in developing integrated methods of assessment based learning curves and detailed engineering assessments is discussed below.

## **2.5 Parametric Modelling**

In parametric cost modelling, the total cost is based upon ascribed physical and performance characteristics and their relationships to component costs. In other words, a functional relationship must be set up between the total cost of the technology and various measurable attributes and characteristics of the product or technology. The relationships which are in the form of mathematical equations are referred to as Cost Estimation Relationships (CER). Parametric models can consist of single or multiple CERs (Bole, 2006; NASA, 2007).

Parametric modelling can be considered as an engineering assessment approach with a lower level of disaggregation. The results of a parametric model depend directly upon the ability of the analyst to establish relationships between the attributes or elements that make up the technology, namely the first job must be to properly choose and then describe the cost influencing factors.

Parametric modelling has been found suitable for assessing technological change in energy technologies in the early stages of development prior to deployment (Thorpe, 1992; Thorpe, 1999). The method has been applied in manufacturing for products in the conceptual design stage (Bole, 2006). Applying parametric modelling in the early design stages can result in a design not only balanced in terms of its engineering characteristics, but also in cost. Unlike detailed models, parametric models can be used where data is limited due to lack of deployment experience for example, by deriving mathematical relationships of cost drivers based on engineering laws related to the technology's physical attributes. The methods can also be useful if alternative concepts need to be explored. This can be achieved by deriving CER for the baseline concept and altering the CER to suit the alternative concepts. Parametric modelling therefore plays a more important role in relative cost analysis compared to absolute cost analysis.



### **2.5.1 Limitations of Parametric Modelling**

In their general form, parametric modelling methods are not ideal for long term forecasts unless very simple CER are used, but this might result in high errors in the cost estimates. Parametric modelling is limited in providing adequate detailed data required for short term strategic decisions necessary in the early stages of a technology where the technological development dynamics are high and costs are not stable. They are highly dependent on the development of CERs. In most cases parametric modelling methods are based on a baseline or analogous concept, in which the analysis may require detailed engineering assessment. Any errors in the detailed definition of this baseline concept will affect the credibility of the parametric models derived from it.

## **2.6 Comparison of Assessment Methods & Discussion**

The learning curve concept is based on deployment and continuity of the technology and does not address the possibility of disruption brought about by innovation also necessary to improve the competitiveness of early stage technologies. Engineering assessment methods, on the other hand, can be used to assess the impact of technological changes in the short term but they lack the ability to forecast into the future as required by investors and policy makers. As a result, the development of methods based on the combination of these may assist in making new emerging technologies more attractive.

Integration of engineering methods into the learning curve involves bringing together useful approaches that have been used for different purposes. However, this can assist towards a more complete representative learning curve for emerging energy technologies. Parametric modelling could be used to integrate learning curves with engineering assessment, taking advantage of their strengths, whilst trying to limit their individual weaknesses. A comparison of learning curves, engineering assessments and parametric modelling is provided in Table 2.1.

|                                | <b>Approach</b>   | <b>Strengths</b>  | <b>Weaknesses</b>  |
|--------------------------------|---|---|--|
| <b>Learning curves</b>         | <ul style="list-style-type: none"> <li>• Cost reduction as a function of cumulative experience</li> <li>• Aggregate in nature, models overall costs based on actual costs</li> </ul>                      | <ul style="list-style-type: none"> <li>• Long term forecasting</li> <li>• Global assessment</li> <li>• Empirical studies backing</li> </ul>                               | <ul style="list-style-type: none"> <li>• Primary concern with outcome rather than process</li> <li>• Lack detail on technology specific causal factors</li> <li>• May overemphasise learning by experience, especially for early stage technologies</li> </ul> |
| <b>Parametric Modelling</b>    | <ul style="list-style-type: none"> <li>• Cost estimates based on mathematical relationships between key variables</li> <li>• Intermediate approach, adjusts for physical or functional changes</li> </ul> | <ul style="list-style-type: none"> <li>• Adaptable for various technologies</li> <li>• Early stages application</li> </ul>  | <ul style="list-style-type: none"> <li>• Limited relevance for long term forecasting</li> <li>• Emphasis on incremental rather than radical changes</li> <li>• Results too dependent on specifying cost estimation relationships (CERs)</li> </ul>             |
| <b>Engineering Assessments</b> | <ul style="list-style-type: none"> <li>• Cost estimates based on detailed analyses of technology or components</li> <li>• Technology specific/project specific approach</li> </ul>                        | <ul style="list-style-type: none"> <li>• Detailed understanding of engineering factors behind cost reduction</li> <li>• Informative for technical improvements</li> </ul> | <ul style="list-style-type: none"> <li>• No relevance for long term forecasting or global assessment</li> <li>• Detailed and robust information required</li> </ul>  |

**Table 2.1 Comparison of learning curves parametric modelling and detailed engineering assessments.**

Learning curves are informative to policy and energy systems modelling, but complementary methods may be necessary to accommodate short term changes to costs due to factors such as technological improvements. The representation of the effect of innovative concepts on the development of learning curves is a step towards adaptation of learning curves of technologies in their early stages of development.

## **2.7 Conclusion**

The chapter reviewed literature on emerging energy technologies and assessment methods for these technologies. Global energy challenges were discussed and emerging energy technologies were found to play an important role in energy mixes that result from efforts of addressing the challenges. These technologies however, are generally more expensive in the initial stages but have the potential to cut costs with

experience as well as technological development brought about by innovation. This potential has been assessed by the use of learning curves, a method used to assess cost reduction brought about by experience in an aggregated way. This method, though beneficial for assessment of cost reduction potential of initially expensive emerging energy technologies, its use has a number of limitations mainly due to its aggregated nature and the need for historical cost data which is not easy to obtain for emerging energy technologies. There also exists a gap in the ability of learning curves to directly address the impact of innovation, a factor also necessary in the realisation of cost reduction potential of emerging energy technologies.

Engineering assessments on the other hand, have the advantage of taking a detailed approach which is crucial for improving cost data methods and disaggregates the assessment to identify cost reduction sources and improve assessment methods for new technologies which might demonstrate short term disruptive behaviour brought about by necessary innovation. Parametric modelling, a medium aggregation approach, might provide the means to model changes brought about by innovation. The development of methods in an integrated approach has the potential to improve assessment methods for early stage technologies.

Learning curves in their simplicity have been applied to energy technologies in previous studies and there has been some research work attempting to address the limitations of their use by considering other methods. It is necessary to consider previous studies where learning curves have been applied to energy technologies and investigate the extent to which other methods have been used to improve the learning curves approach. The application of learning curves to energy technologies together with methodological issues associate with their use and development are addressed in the next chapter.

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## 3 Existing Assessment Methods

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### 3.1 Introduction

This chapter aims to further explore the application of cost assessment methods to emerging energy supply technologies through the review of some relevant studies which exist in literature. Case studies where learning curve methods have been developed and/or applied in their simple form, or improved through the use of engineering based and other supplementary methods are used for the review. The chapter will also discuss major associated in the development and use of learning curves. In addition, relevant literature that reviews energy technology learning curves is also used to get an understanding of typical learning rates of emerging energy technologies which will serve to provide possible benchmarks for the results of improved assessment methods proposed at the end of this chapter.

The next section, 3.2, outlines how learning curves have been used for energy technologies, highlighting important factors that need to be taken into account in learning curves development. The application of the two factor learning curves (2FLC) is also described in section 3.2. Section 3.3 looks at previous studies where learning curves were used in conjunction with complementary methods: engineering assessment methods, parametric modelling and other relevant approaches. Section 3.4 provides a brief technology based review of the use of learning curves, providing typical learning rates for emerging energy technologies. This is followed by a discussion of the application of assessment methods for emerging energy supply technologies, leading to the discussion of the proposed approach for the development of improved assessment methods for this study. Finally, section 3.6 concludes the chapter.

## **3.2 Development of Learning Curves for Energy Technologies**

Various researchers have studied the application of the learning curve method of assessment to emerging energy technologies and some have gone further to develop learning curves for the technologies that are used for forecasting future costs. The application of learning curves for emerging energy technologies initially gained popularity in the early 2000s. The major credible work that was the reference for most early studies is the book published in 2000 by the International Energy Agency (IEA) which gave guidelines for learning curves for energy technology (IEA, 2000).

In 2001 McDonald and Schrattenholzer carried out work with the aim of providing an empirical basis for choosing reliable estimates of learning rates for a number of energy technologies. This was one of the early attempts of compiling a database of energy technologies learning rates. They assembled data for a variety of energy technologies using different sources and estimated the implied learning rates using the classic learning curve model for different countries. Conclusions were then drawn on incorporating the resulting learning rates in energy models (McDonald and Schrattenholzer, 2001). More recent work by Junginger et al. (2010) gives a thorough review of the theory and application of learning curves and covers a number of cases of energy technologies, presenting the ranges of learning rates in the literature.

Several types of learning curves have been developed or adopted for different technologies using different methods and approaches. In general there are agreements in the ranges of the published learning rates and cost reduction trends of technologies. However, variabilities in the specific learning rates are observed mainly due to differences in the approaches taken in the development of the learning curve methods. The section below discusses the construction of learning curves for energy technologies, focussing on the important factors and parameters.

### **3.2.1 Construction of Learning Curves**

The development of learning curves is a process that requires careful consideration of the critical factors that underpin the construction and/or the use of learning curves

and learning rates. Variations in estimated learning rates for the same technologies published in literature exist (Junginger, Van Sark et al., 2010; Green-X, 2012) and can be mainly attributed to differences in the choice of:

1. geographical boundaries
2. independent variable to represent experience
3. dependent variable to represent cost reduction

These three interrelated factors are dependent on the technology in question, data availability and the purpose of the analysis.

Three main stages in learning curve development can be defined as: data gathering, data processing and analysis of the learning curve and learning rates (Neij L, Andersen P.G et al., 2003). The acquirement of relevant and good quality data underpins the development of useful learning curves for energy systems modelling. The main data is required for the independent variable that represents experience on the x-axis, such as cumulative installed capacity, and the dependent variable that represents cost on the y-axis on the learning curve. Data can also be gathered for validation purposes where the modelled learning curve is fitted on market data. The type of data available is dependent on the technology's level of establishment on the market. Search for data for emerging technologies can be difficult as historical data is limited and most reliable data is not always publicly available.

Good sources of data sources are important for the integrity of the resulting curves and learning rates. Databases collected by government funded organisations are usually used because data owned by private companies is often commercially sensitive. Where possible, data needs to be checked and verified and in some cases even scrutinised by experts (Neij L, Andersen P.G et al., 2003). If data sources are limited, there might be a need to obtain data through other means such as cost estimation methods based on knowledge of the technology's attributes and characteristics. Another approach is to use analogous methods that make use of data from similar technologies.

Data processing involves learning curve calculations of cost and cost reduction or derivation of learning rates. This process begins with the choice of the appropriate type of learning curves to use or to construct. The choice of processing methods is influenced by the kind of data that is available and the purposes of the learning curves. The purpose is be related to the user of learning curves, and energy technology learning curves are mainly intended for the following audience (Neij L, Andersen P.G et al., 2003):

1. Policy makers
2. Researchers
3. Investors
4. Manufacturers

The third stage in development and use of learning curve methods involves the analysis of technology costs and cost reduction potential, mainly by the use of learning rates. The comparison of learning rates of technologies using different learning curve methods or comparison of learning rates of different technologies make up the greater part of learning curve analysis. Analysis might also involve validating modelled learning curve results by comparisons with real data. Sensitivity analysis allows the exploration of the results in the context of the assumptions made or the possible scenarios.

### **3.2.1.1 Global and Local Learning Curves**

Learning curves are generally distinguished as global and local learning curves, according to the geographical boundaries (Junginger, Van Sark et al., 2010; Wiesenthal, Dowling et al., 2012). Global assessments use data for the whole globe, whereas the local learning curve used data that is either local to the company or to the country. Learning curves have been constructed based on data for regions such as the European Union, and these can be considered as local learning curves.

IEA (2000) suggested that strategies should be founded on long term collective efforts based on international cooperation. The global approach allows the possibility of the integration of the effects of knowledge spillovers between countries (Jamash,

2006). It has more relevancy for climate change models which have to deal with global impacts and therefore, most suitable for energy technologies (Junginger, Van Sark et al., 2010).

The use of global information is, however, not ideal for reflecting technological changes and is limited in providing information on the impact of production or performance improvements. Although knowledge transfer takes place globally, technology is developed and deployed at a local level. Policies and regulations differ in countries and measures and strategies to map out the future of emerging energy technologies are usually country specific. Moreover for renewable energy technologies resources such as wind speed for wind energy vary for different locations or between countries in general. Data type and quality therefore vary across countries because of country specific factors such as different policy and regulation thus, making local learning curves more attractive. Furthermore, it is a challenge finding cost data that is representative of the global status.

Global learning curves are commonly used because of data limitations for localised learning curves (Junginger, Faaij et al., 2005) and the relative ease of availability of global data from relevant national and international institutions and organisations. For example, wind energy organisations such as the Global Wind Energy Council (GWEC) keep records of global cumulative capacity of wind energy. An alternative approach is to combine both local and global data, for example, by using global cumulative installed capacity and local cost data.

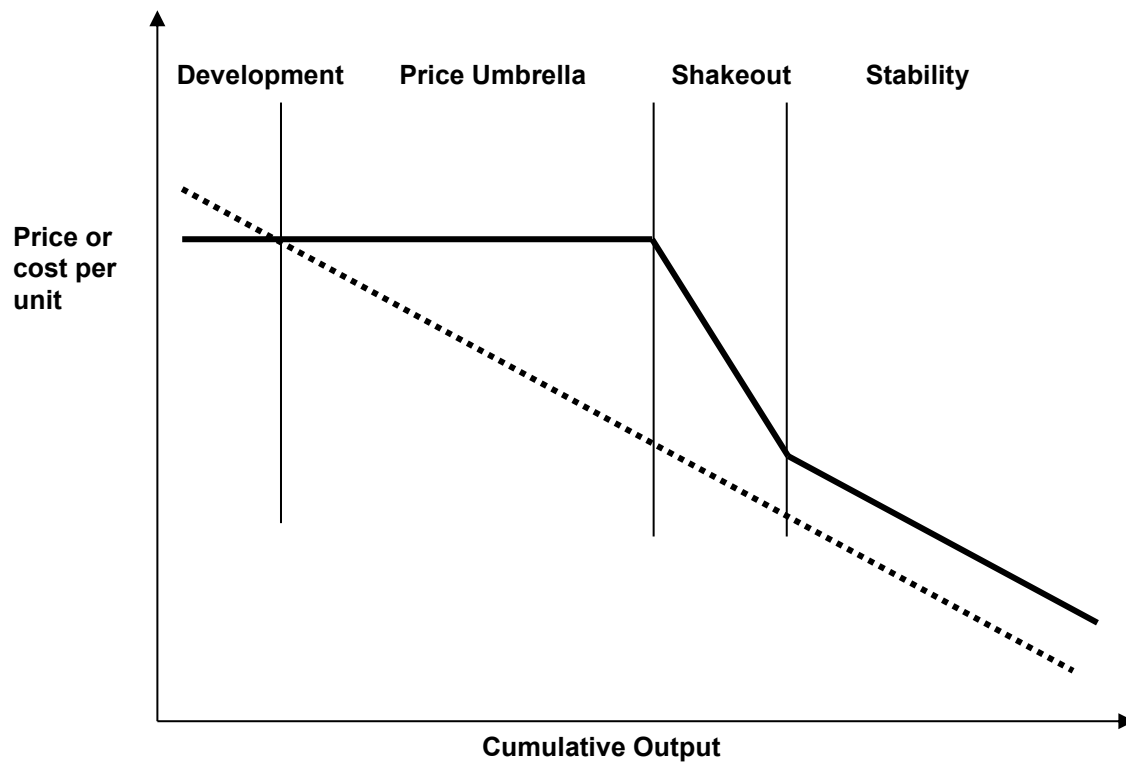
McDonald and Schrattenholzer (2001) collected data mainly from OECD countries namely the US, Denmark, Germany and Japan as well as other countries such as Brazil, for developing an empirical learning curves database of energy technologies. Neij L. et al. (2003) carried out the European wind energy EXTOOL project that developed learning curves using data from countries leading in wind energy. Relevant data was found for Denmark, Germany, Spain and Sweden, but could not be found for UK and Netherlands. The use of the 4 countries was justified by the fact that these four contributed 85% of installed capacity in Europe at the beginning of 2001.



Using the case study of wind energy, the EXTOOL project report suggested other ways of categorising learning curves, in addition to geographical boundaries. Firstly, learning curves can either represent one of two perspectives, *market perspective* - based on installed technology in different countries or electricity generation in different countries, or *production perspective*-based on production such as wind turbines produced from different countries. Additionally learning curves can take the *systems approach*-a more technology detailed approach where the system is divided into individual components which make up the technology such as wind turbines and balance of station (BOS) components (Neij L, Andersen P.G et al., 2003; NEEDS, 2006)

### **3.2.1.2 Cost – Price factor**

In theory the learning curve concept describes cost rather than price as a function of cumulative production (Neij, 2008). Cost data is more representative of technological change as it is not directly affected by exogenous market factors. However, as price data is more readily available than cost data, it is commonly used to construct learning curves, based on the assumption that a certain relationship exists between price and cost. This relationship is dependent on technology maturity and a healthy supply and demand. However, in the early stages of development, as the product is still getting established on the market, the cost–price relationship changes over time. Figure 3.1 is a typical and common illustration of the price and cost development, produced by Bolton Consulting Group (BCG) in 1968. The dotted line represents the cost whereas the solid line represents market price dynamics.



**Figure 3.1** Price-cost relations for a new product, Boston Consulting Group, 1968 (IEA, 2000)

The four stages of price dynamics are explained below (Junginger, Van Sark et al., 2010):

- 1. Development:** Product is introduced at a lower price than the costs of the other technologies on the market.
- 2. Umbrella:** As the volume of the product increases the costs drop, resulting in increasing profit margins which stimulate new entrants and competition.
- 3. Shakeout:** Price declines rapidly for a short period due to competition.
- 4. Stability:** Prices and costs decline at the same rate. Long term stability is not guaranteed and factors such as changes in the demand, supply constraints or policy changes in the case of energy technologies might cause new umbrella or shake out phases to occur.

Price becomes a relatively more reliable variable to replace cost only in the stability phase and is therefore used in a number of studies with a degree of confidence in that stage. However, price fluctuations are bound to exist even beyond the early stages when technology is established on the market. The research community is aware of this, but still use price data, because cost data is hard to find (Junginger, Van Sark et al., 2010). The price–cost factor has been found to be one of the main reasons for the variability in the calculated learning rates of different technologies (McDonald and Schrattenholzer, 2001; Alberth, 2008). It is also interesting to note that even the cost does not always reduce at a constant rate but the cost reduction trend (represented by the dotted line in Figure 3.1) can be subjected to disruptions in the short term. Technologies are complex systems made up of components sourced from the supply chain therefore technology costs can be indirectly affected by supply chain prices (Wiesenthal, Dowling et al., 2012). For example, sudden increases in raw material prices can have an impact on wind turbine components such as the gearbox resulting in increased wind energy technology costs.

Global learning curves are typically constructed using data based on price although the price would normally refer to a particular country or currency, usually US dollars or Euros (€). Studies that estimate cost of energy data, such as the Marine Energy Challenge (MEC) by Carbon Trust UK, are generally site specific or at least country specific (Callaghan and Boud, 2006). The performance of an energy technology is site specific depending on the local resource. In such cases local data can be used to support global data.

### **3.2.1.3 Time Dependency**

Classical learning curve analysis does not factor in time directly, but development of a technology in reality is time dependent. The relevance of learning curves can be improved by taking into account the time period being referred to, as well as the length of analysis. The choice of the analysis timeframe is dependent on the data available as well as the purpose of the learning curves being developed. Learning curves developed over long timeframes are most desirable but relevant historical data is not always available. Disruptions such as changes in market prices of raw

materials might affect the cost reduction anticipated. Some of the impacts might not be significant in the long term, but in some cases overlooking these factors might result in learning rates that have uncertainties.

McDonald and Schrattenholzer (2000) assembled data on experience accumulation and cost reductions for a number of energy technologies and estimated learning rates of 26 data sets. The average period of study for the different technologies was 15.3 years, with the longest time frame being 30 years, for solar photovoltaics (PV) modules. Nemet (2006) used a 26 year period of study for a cost model for solar photovoltaics (PV) learning curves (1975 and 2001). To improve the fit of the data the period of study was divided into two, a period before and a period after 1980. Junginger et al (2004) carried out a learning curve assessment, complemented with engineering assessments to forecast energy costs, for a timeframe of 16 years to 2020.

When market data does exist, statistical methods can be used to analyse variability in the learning rates. An analysis of learning rates derived from market data and those calculated from methods presented in the literature should be performed, so as to evaluate their usefulness for application in long-term energy models (McDonald and Schrattenholzer, 2001).

### **3.2.2 Two Factor Learning Curve (2FLC) Models**

As discussed in Chapter 2, one approach to distinguish the impact of R&D efforts on learning effects involves the construction of 2FLC (Kouvariatakis, 2000). A study was carried out in 2005 to analyse the impact of R&D on wind energy innovation in Denmark, Germany and the UK (Klaassen, Miketa et al., 2005). They took an approach similar to that used in an earlier study for modelling market experience and R&D impacts for energy systems models (Barreto and Kypreos, 2004). This involved a quantitative analysis of R&D and capacity expansion on innovation using a 2FLC model. Klaassen et al. (2005) distinguished their empirically based work by focussing on the quantification of policy instruments on innovation for wind energy.

Knowledge stock was introduced as an extra parameter in the learning curves equation. This parameter took into account the depreciation of cumulative knowledge stock and added a time lag between the actual R&D expenditure and their addition to the knowledge of stock, which was defined by the equation.

$$K_t = (1 - \delta)KS_{t-1} + RD_{t-x} \quad 3.1$$

Where,  $K_t$  is the R&D based knowledge stock at time  $t$ ,  $RD_{t-x}$  is the R&D expenditure, at  $t-x$ , where  $x$  is the time lag for adding R&D to the knowledge stock and  $\delta$  is the annual knowledge stock depreciation.

The resulting 2FLC equation modified from the classical simple learning curve equation given in equation 2.1 is given below:

$$C_t = C_0 q_t^{-b} \times K_t^\beta \quad 3.2$$

Where  $C_0$  is the cost of the first unit,  $q_t$  is the cumulative capacity at time  $t$ ,  $\alpha$  is experience index used to estimate the learning rate due to experience (learning-by-doing ( $LD$ )) and  $\alpha$  is the experience index due to knowledge stock (learning-by-searching ( $LS$ )). The two learning rates due to these factors were estimated using the following:

1. Knowledge stock learning rate

$$LS = 1 - 2^{-\beta} \quad 3.3$$

2. Cumulative capacity learning rate

$$LR = 1 - 2^{-b} \quad 3.4$$

Time-series data was collected for the three countries (Germany, Denmark and the UK) and used to estimate parameters of the 2FLC model. The analysis was restricted to an evaluation of public R&D, with no consideration of private R&D efforts, because it is difficult to obtain private sector data. Robust estimations of a learning-by-doing rate of 5.4% and a learning-by-searching rate of 12.6% were determined

from the study. It was noted that there could have been an overestimation of the impact of public R&D expenditure. An earlier study by Crique et al (2000) suggested that private R&D expenditure for the period 1974-1999 might have been 75% higher than public. More detailed country analysis is required to explain spillover effects due to imports and exports, which were found to be significant.

Jamasb (2006) proposed another method of developing 2FLC whereby R&D spending was treated as a variable similar to cumulative production. In addition the role of R&D was also estimated by the use of knowledge stock gained in the form of a number of patents. The model consisted of a system of simultaneous equations incorporating both R&D and cumulative capacity to transform the learning curve into a learning-innovation-diffusion model (Jamasb, 2006). In the model for estimating unit cost  $C$  (€/KW), cumulative production  $q$  (MW) was treated as an endogenous factor. R&D spending  $RD$  (mil€) and time variable  $Y$  were treated as exogenous factors. Cumulative number of technology patents  $P$  and a proxy for knowledge stock  $k$  were also added as additional instrumental endogenous variables that could be used instead of the time variable  $Y$ . For technology  $n$  over learning period  $t$ , the 2FLC equation and the diffusion equation are given below.

Two factor learning equation:

$$\log C_{nt} = \alpha_n + \beta_n \times \log RD_{nt} + k_t \times \log q_{nt} \quad 3.5$$

Diffusion equation:

$$\log X_{nt} = \mu_n + \omega_n \times \log X_{nt} + X_t \times \log Y_{nt} \quad 3.6$$

Using this model, the learning effect in thirteen different energy technologies was assessed. The choice of technologies studied was driven by availability of suitable data. As the aim was to examine high level patterns of technical change, aggregated global data was used. This had an advantage of accounting for spillover effects, but it cannot be used for examination of the effect of policies and local circumstances, which require country or regional studies. The costs were expressed in \$US at 1999 levels, and technology patent data was obtained from the European Patent Office.

The results suggested that the effects of learning-by-doing and learning-by research can be considered independent from each other. The conclusion of this study by Jamasb in 2006 was that extensive and accurate data is needed for improved 2FLC models.

2FLCs allow accommodation of the role of R&D but result in complex models or equations. These require more detailed data, which is limited for emerging energy technologies. The models are still being developed and there is not a standard method of constructing learning curves. The approaches discussed above by Klaassen (2005) and Jamasb (2006) are different in their definition of R&D efforts. The choice of variables to represent experience in learning curves models still raises questions when developing a 2FLC. A study by Barreto and Kypreos (2004) came to the conclusion that although the 2FLC is a helpful step towards the development of a more consistent representation of the technological learning process, there was still a long way to go in disentangling the role of R&D in the energy innovation system. There is limited evidence of recent work in developing more credible 2FLCs.

### **3.3 Complementary Assessment Methods**

As discussed in the previous chapter, the application of learning curves is associated with a number of limitations. It is agreed in a number of studies that the use of learning curves requires complementary methods that try and disaggregate the system to some extent, to unravel sources of cost reduction. The use of bottom-up analysis methods have been found to capture uncertainties that are not captured in learning curves (NEEDS, 2006). For the purposes of this study complementary methods are distinguished as qualitative engineering assessments, quantitative engineering assessments, or parametric modelling based methods. Other methods that relate cost to technology and physical attributes are also considered.

Chapman and Gross (2001) showed that engineering based approaches provide enhanced insight into the drivers of cost reduction and possibly potential discontinuities in learning curves. Though variabilities in the definition and use of such complementary assessment methods might exist, what they have in common is that they all take an alternative bottom-up approach to technology assessment

compared to the aggregate top-down nature of learning curves. When used with learning curves, such complementary methods have been found to result in improved technological forecasting for energy technologies.

### **3.3.1 Quantitative Engineering Methods**

The identification of a technology's cost drivers and quantification of cost reduction for the different components is crucial for assessing the competitiveness of emerging energy technologies. Quantitative cost methodologies based on engineering principles can be very detailed and technological specific, requiring vast amounts of resources and modelling work. The application of highly disaggregated detailed methods, together with learning curve assessments, to emerging energy technologies is limited in current literature. The methods are typical in engineering design and new product development. However, the principles have been applied in some studies for identifying and estimating possible cost reduction in a disaggregated way to some extent. The use of analogous costing is common, whereby cost reduction is estimated using more established technologies with cost centres similar to the technology in question.

Junginger (2004) carried out a study motivated by the need to assess the cost reduction potential of offshore wind. The study analysed technological developments and cost reduction trends in both the offshore and onshore wind sectors. Cost reduction was quantified using learning curves and quantitative engineering methods. The study was based on initial investment costs, which constitute nearly 70% of the cost of electricity. It was found necessary to analyse technological developments of different components separately because the construction of offshore wind farms can build on the experience from various other industrial sectors, such as offshore oil and gas industry, thus making use of the so-called analogous assessments. Four main components were assessed separately: wind turbines, foundations, grid connection, and the installation process, and learning rates were estimated for each of the components. The learning curves of offshore turbines were assumed similar to those of onshore turbines. (Junginger, Faaij et al., 2004). The results of the study are shown in Table 3.1.



| Component     | % of Total Costs | Progress Ratio % | Comment   |
|---------------|------------------|------------------|---|
| Wind turbines | 30-50            | 81-85            | Based on various onshore wind turbines both global and national                           |
| Grid          | 10-15            | 62               | Based on global HVDC cables installed found in literature                                 |
| Foundations   | 5-10             | 90-95            | No experience curve, based on cost development of steel, main raw material                |
| Installation  | 0-5              | 77               | Installation days vs. number of turbines installed. Case study of 2 wind farms in Denmark |

**Table 3.1 Progress Ratios of offshore global wind farms (Junginger, Faaij et al., 2005)**

A European Union study suggested a way of improving the application of learning curves by taking a multiple method approach. The study was carried out as part of work performed within the *New Energy Externalities Developments for Sustainability* (NEEDS) project (NEEDS, 2006; Neij, 2008). The methodology was based on learning curves, bottom-up analysis and estimation of sources of cost reduction. Learning curves were proposed using installed capacity in kW as a measure of performance. Data was sourced from a large number of studies, and learning curves were based on real cost/price data from these sources. Quantification was therefore based on available historical data, mainly price data rather than cost data due to lack of the latter. The bottom-up approach was used to describe figures estimated for a medium term range for wind turbines, photovoltaics, solar thermal, fuel cells, nuclear power, advanced fossil fuel technologies and bioenergy technologies. The study suggested approximate learning rates for the technologies. Tentative learning curves were suggested for technologies such as bioenergy, where development of learning curves was limited. The results of the learning curves and bottom-up analysis agreed in most cases. The bottom-up analysis also confirmed large uncertainties not revealed by learning curves, such as their inability to take into account physical limitations or changes in the market (NEEDS, 2006).

Detailed Engineering methods have been used to derive costs of the components of an energy device based on the physical attributes of the technology. The “Sunderland Model” is commonly known for detailed engineering cost assessment of wind turbines from the first principles (Harrison, Hau et al., 2000; Manwell, McGowan et al., 2002; Fingersh, 2006; Maples, Hand et al., 2010; Rivkin, Toomey et al., 2012).

The original Sunderland model was developed for the United Kingdom's Department of Energy (DOE) in the 1980s. An effort by researchers at the University of Sunderland in the UK resulted in a set of scaling tools for machines with rotor diameters ranging from 15 m to 80 m (Harrison and Jenkins, 1993). The approach allows detailed cost assessment of turbines based on estimated weights of turbine components which are estimated based on the physical attributes and design drivers of these components. The model was updated in the late 1990s to allow for the growth of turbines take into account the growth of commercial wind turbines from kW to MW sizes (Rivkin, Toomey et al., 2012). Recent use of the model include wind turbine cost scaling studies at the US National Renewable Energy Laboratory (NREL) (Bywaters, John et al., 2005; Fingersh, 2006; Maples, Hand et al., 2010).

### **3.3.2 Qualitative Engineering Methods**

Qualitative analyses provide insight for more focused strategies and policies for both policy makers and industry. This analytical approach can be achieved through researching and analysis of technology studies to identify, and have enhanced understanding of, possible sources of cost reduction. Technologies can also be assessed by way of comparison with other similar technologies. Qualitative methods can be useful in cases where there are limitations in quantitative data methods and also for non-standard products or processes. The results of qualitative assessments are important for supporting learning curve analysis or other quantitative approaches.

One approach to qualitative analyses is the use of expert opinion by way of interviews. Junginger et al. (2004) carried out qualitative analysis of offshore wind turbines, in addition to quantitative methods described above in a bid to improve learning curves of this relatively new energy technology. Literature was scanned and interviews were held with experts from research institutions, offshore contractors and producers of offshore equipment, for qualitative information on past and current trends and possible cost reduction opportunities. In some cases the experts were asked to estimate ranges of possible cost reductions within their particular expertise. The NEEDS project carried out in 2008 also involved an expert judgemental method based on interviews to forecast long term alternative costs for solar PV and wind.

The methods identified actual and perceived sources of cost reduction and the potential range of future costs as well as associated uncertainties.

Chapman and Gross (2001) analysed the economic and technical prospects for renewable energy generating technologies for the UK to 2020 by taking a qualitative view together with learning curves for solar photovoltaics (PV), wind and energy crops. The work was based on analyses by the then Department of Trade and Industry (DTI) in 1994 and 1998 (Chapman and Gross, 2001). The engineering assessment of technology potential placed the technologies on a spectrum that ranged from mature to emerging technologies. Cost reduction potentials for emerging technologies were identified by benchmarking with similar technologies in the same category whose technological progress was known. Experts in other areas such as economics, innovation and policy making can be consulted to provide valuable information for holistic analysis of cost reduction potential of technologies. However, this type of qualitative approach is too dependent on the judgement of the expert, which might differ from one expert to another.

The common ground for engineering assessments is a bottom-up approach that endeavours to isolate sources of cost reduction. Qualitative analyses support quantitative methods that estimate costs. Generally, engineering assessments provide short term more technological specific information, although some qualitative analyses can give longer term insights.

### **3.3.3 Parametric Modelling Application**

There is limited case study evidence of the use of parametric modelling in emerging energy technologies, a method ideal for early stage technologies. Atkins (1992) and Thorpe (1999) used parametric models to compare electricity production costs of wave energy devices.

Nemet (2006) carried out a study to understand the drivers behind technical change in solar photovoltaics (PV) by disaggregating historic cost reductions into observable technical factors (Nemet, 2006). It suggested that learning derived from experience was only one of several explanations of cost reduction, and seven distinctive cost

affecting factors were identified for the technology. A parametric based model was then used to determine cost reduction due to each factor over a year by developing mathematical relationships between cost and the factors. The individual contributions were then summed up to give the total cost reduction over a year for the technology. Nemet (2006) used PV production data only and did not consider balance of station (BOS) costs to simplify the model. Due to the quality of the data and the exclusion of exogenous factors such as interest rates, the changes in cost could only be applied to the capital cost of PV and not to the cost of electricity produced.

Interestingly, the Nemet (2006) results suggested that learning effects due to cumulative production did not appear to have been major factors in enabling cost reduction for PV. Learning-by-doing did not play a major role in the 3 major factors which accounted for 60% of the estimated cost reduction, but in others factors which only accounted for 10% of overall change in cost. The results illustrated the weakness of the learning curve in explaining cost reductions for PV, and highlighted the need for complementary models to enhance understanding of future technical improvements. It was concluded that careful consideration should be taken on the reliance on learning curves when making assumptions for future scenarios (Nemet, 2006).

In a systems based approach, Coulomb and Neuhoﬀ (2006) used an engineering assessment model to capture the cost changes of wind turbines due to scaling, by breaking down the turbine into components. The analysis of cost how turbine costs scaled with size, in terms of the rotor diameter, was based on parametric modelling principles, and mathematical relationships between cost and size were developed. This method was developed for upscaled turbines and did not take into account the impact of other cost drivers that come with innovation, such as component design changes and improvements. Individual component costs were not modelled, but overall turbine costs, together with component cost shares, were used in the mathematical models that related cost to turbine size. Due to limitations in cost data, the improved cost model was plotted with turbine price data from German manufacturers and the model had a better fit than the simple learning curve (Coulomb and Neuhoﬀ, 2006).

### 3.3.4 Other Methods

Energy supply technologies have been compared using other metrics based on their performance, in addition to cost assessments. The viability of a technology is not only reflected in the cost of the technology, but also in the delivering of the output in a sustainable way. Other approaches to engineering assessments or parametric modelling, that relate a technology's physical attributes to cost or output, have been found to have the potential to enhance methods of analysing and forecasting technological potential of emerging technologies.

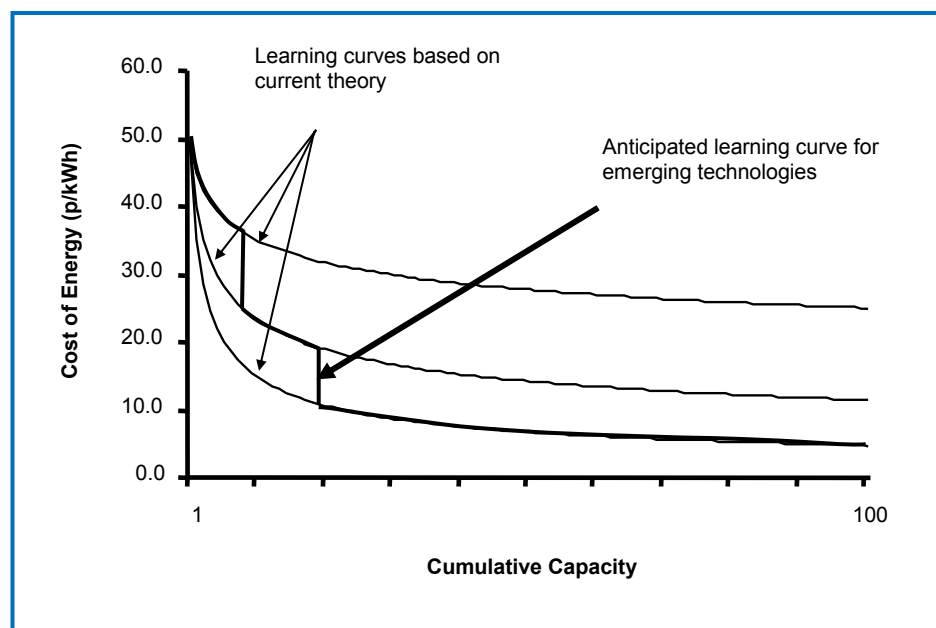
Stallard et al. (2008) described and used Data Envelopment Analysis (DEA) for wave energy technology, a relatively new technology. This is an alternative engineering based approach to assessing which uses mathematical based methods to compare devices for different sites, based on parameters derived from common components (Stallard, Rothschild et al., 2008).

Wave energy is not yet established on the market and in the absence of detailed data it is difficult to predict capital costs, the basis of learning curve construction. However, for different wave energy converters, similar non-device specific components exist. Stallard et al. (2008) made the assumption that these non-device specific components, such as civil infrastructure, scheme overheads, electrical infrastructure and scheme O&M, are the same irrespective of the detailed designs, thus simplifying the modelling. The method was applied to four categories of wave energy converter (WEC) and eight different wave climates to identify combinations most likely to be economic. A hypothetical WEC was used to specify the amount of electricity as the output. This method was used for comparative purposes for the devices and site characteristics. Rather than giving a snap shot of the cost of a particular design, it allowed identification of designs that convert given resources efficiently. (Stallard, Rothschild et al., 2008). Although this method was not used for the improvement of learning curves, DEA is applicable to early stage designs and some of the methodological approaches used might be useful for this study.

In another study in 2004, a method for integrating innovation and learning curves approach was developed after the identification of the need for a firmer theoretical

base for making learning curve predictions for immature and emerging technologies (Linton and Walsh, 2004). This study introduced the idea of *physical limits* to progress. These barriers may be overcome through innovation resulting in cost reduction or performance improvements (Mukora, Mueller et al., 2009). The potential to overcome such barriers is related to technology trajectories and roadmapping. The idea of physical barriers has not been considered much in the research literature. However, the barriers can be viewed not necessarily as a physical limit but rather any conceptual change in the technology that is introduced to improve the technology's economic competitiveness so as to reach parity with conventional sources.

On a learning curve as illustrated in Figure 3.2, overcoming a barrier is anticipated to enable a step change down to a lower curve resulting in a discontinuous learning curve. If the movement from one curve to another is modelled, a possible learning curve for emerging or immature technologies is obtained (Linton and Walsh, 2004)



**Figure 3.2 Proposed ideal learning curves for emerging technologies Source: adapted from Linton and Walsh (2004)**

The analysis of the limits and barriers for different components can result in the identification of not only different pathways for the technology, but also possible

incremental and radical design improvement changes. Overcoming limits is associated with changes which might result in shifts between learning curves. Though current academic research offers little insight into movement between such curves, successful roadmaps in other sectors suggest the possibility of modelling these shifts (Linton and Walsh, 2004). Though it is not yet possible to construct a family of curves, and the transition from one curve to another, it is possible to gain insights into the shape of a curve for emerging technologies. In some cases barriers or enablers might not necessarily be physical, but other parameters that limit or enable improvement such as policy mechanisms, regulation or market factors.

In summary, learning curves have been used in their simple form or together with other approaches. Table 3.2 summarises relevant studies that made use of the assessment methods discussed above.

| Reference                            | Learning Curves | Engineering Assessments | Parametric Modelling |
|--------------------------------------|-----------------|-------------------------|----------------------|
| (McDonald and Schrattenholzer, 2001) | ✓               |                         |                      |
| Neij et al (2003)                    | ✓               |                         |                      |
| (Klaassen, Miketa et al., 2005)      | ✓ (2FLC)        |                         |                      |
| (Jamasb, 2006)                       | ✓ (2FLC)        |                         |                      |
| (Nemet, 2006)                        |                 | ✓                       | ✓                    |
| (Callaghan and Boud, 2006)           | ✓               | ✓                       | ✓                    |
| (Coulomb and Neuhoff, 2006)          | ✓               | ✓                       | ✓                    |
| (Chapman and Gross, 2001)            | ✓               | ✓                       |                      |
| (Junginger, Faaij et al., 2005)      | ✓               | ✓                       |                      |
| (Neij, 2008)                         | ✓               | ✓                       |                      |
| (Stallard, Rothschild et al., 2008)  | ✓               | ✓                       | ✓                    |
| (Linton and Walsh, 2004)             | ✓               | ✓                       |                      |

**Table 3.2 Application of different assessment methods**

### 3.4 Emerging Energy Technology Learning Curves

This section focuses on the use of learning curves for specific early stage low carbon electricity supply technologies and overview of their cost reduction trends. Table 3.3

further explores the relevant studies on the use of learning curves for different technologies.

| Work   | Sources of Data                          | Technology                         | Learning mechanism                                    |
|--|--|------------------------------------|---|
| (McDonald and Schrattenholzer, 2001)                     | Global price                             | 26 Energy technologies             | Learning-by-doing                                     |
| (Jamasb, 2006)   | Global price                             | 13 Energy technologies             | Learning-by-research and learning-by-doing            |
| EXTOOL (Neij L, Andersen P.G et al., 2003)               | Germany, Sweden, Denmark, price          | Wind                               | Learning-by-doing                                     |
| (Klaassen, Miketa et al., 2005)                          | Germany, Denmark, UK                     | Wind                               | Leaning-by-searching                                  |
| (Nemet, 2006)  | Global                                   | Solar PV                           | Complementary bottom-up based parametric model.       |
| (Coulomb and Neuhoﬀ, 2006)                               | Germany price lists and. global capacity | Wind                               | Learning-by-doing                                     |
| (Chapman and Gross, 2001)                                | Global for UK analysis                   | Renewable Technologies             | Learning-by-doing                                     |
| Marine Energy Challenge (MEC) (Callaghan and Boud, 2006) | Costs calculated                         | Wave                               | Learning-by-doing,                                    |
| (Junginger, Faaij et al., 2004)                          | Global                                   | Offshore Wind                      | Initial investment costs- 4 separate component curves |
| (Neij, 2008)   | Global                                   | New Electricity Generation Sources | Data collected from a number of studies               |
| (Stallard, Rothschild et al., 2008)                      | UK and US                                | Wave                               | Matching site and device                              |
| (Junginger, Van Sark et al., 2010)                       | General review                           | All energy technologies            | Extensive review book for energy sector learning      |

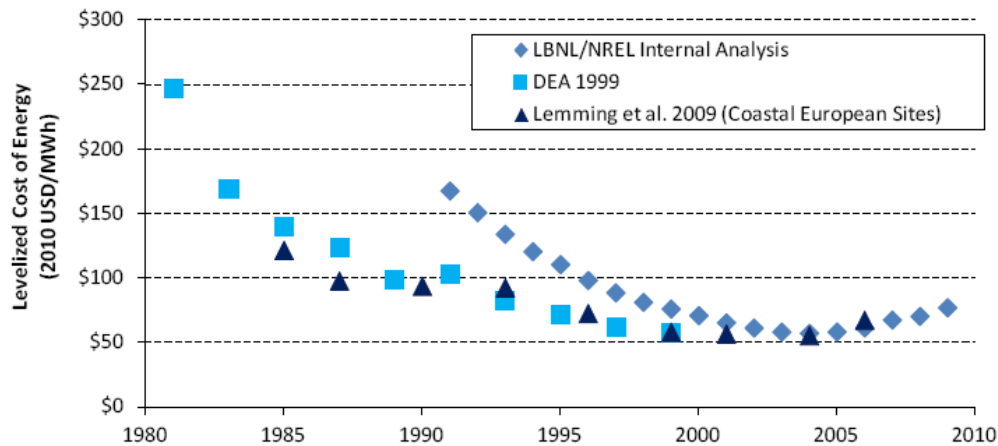
**Table 3.3 Summary of Major Studies on Energy Technology Learning Curves**

Emerging energy supply technologies on the market particularly onshore wind, offshore wind, solar photovoltaics and bioenergy have generally shown strong cost reduction trends since deployment. Numerous and different historical learning curves have been devised (developed or suggested) for the major energy technologies as given in Figure 2.4 and 2.5 (Junginger, Van Sark et al., 2010).

The cost reduction and cost dynamics vary for different technologies and for different periods of time. However, there was a common cost reduction pattern for the majority of technologies including fossil fuel based technologies for the period



from around 2002 to 2008 when sudden cost increases were observed as illustrated by Figure 3.3 for wind energy.



**Figure 3.3 Wind energy cost trends. (Lantz, Wiser et al., 2012)**

This was mainly due to the increase in energy demand, particularly for renewable energy technologies, increasing raw material prices and also rises in the prices of fossil fuel based conventional technologies (Junginger, Van Sark et al., 2010). These market related factors had an impact on the cost reduction potential historically forecasted in energy systems models and caused disruption in learning curves. The author is not aware of the evidence of this being fully modelled and accounted for in classical learning curves as yet. After 2008 costs began to reduce again and this may be attributed to the onset of the financial crisis in the second half of 2008, which to some extent caused a reduction in demand. The prices of steel and other raw materials also started to decline around 2008 thereby resulting in reduced cost for most technologies (OECD, 2009).

Junginger (2010) suggested that it may be argued that though cost or price increases were felt, there is no evidence that learning stopped, but was rather overshadowed by market factors. This raises questions on the issue of cost increases and negative learning curves, whether cost increases imply negative learning or in some cases learning merely overshadowed by other factors. Observed increasing material costs had an impact on production costs resulting in short term impact and these are not accounted for.

McDonald and Schrattenholzer (2001) suggested a wide range of learning rates for energy technologies with a median range around 17%. The range was not very far from that compared to manufacturing range of 19-20% and this analogue was useful in the early days until more detailed energy studies were available (McDonald and Schrattenholzer, 2001). The EU NEEDS project reported learning rates in the range 0 to 20% (progress ratios of 80% to 100%) for energy technologies (NEEDS, 2006).

Published learning rates vary significantly across various studies and data sets (Nemet, 2009; Junginger, Van Sark et al., 2010; Wiesenthal, Dowling et al., 2012). Given below is an overview of cost reduction trends for onshore wind, offshore wind, solar PV, marine technologies and bioenergy.

### **Onshore wind energy**

Onshore wind with an average annual growth of 27% over the past decade is among the most cost-competitive of renewable energy sources and can now compete without special support in electricity in some markets (IEA, 2012). There is a clear cost reduction trend from 1990 to 2004 followed by the historic increases experienced by nearly all technologies up to around 2008 when cost reduction resumed. The rise of wind turbine prices between 2000 and 2007 is considered modest compared to the rise in pulverised coal plants, which increased more than 70% (Hamilton, Herzog et al., 2009; Junginger, Van Sark et al., 2010).

European Union, EXTOOL and NEEDS projects carried out extensive work based on the use of learning curves and complementary methods for onshore wind (Neij L, Andersen P.G et al., 2003; NEEDS, 2006; Neij, 2008).

Table 3.4 summarises studies on onshore wind learning and the learning rates from the studies.

| Authors                            | LR   | Global or Local                            |  | Timeframe  |
|------------------------------------|------|--|--|------------|
|                                    |      | Independent Variable (Cumulative Capacity) | Dependent Variable (Cost)                    |            |
| (Neij, 1997)                       | 4    | Denmark                                    | Denmark (turbine cost)                       | 1982-1985  |
| (Mackay and Probert, 1998)         | 14   | USA  | (turbine cost)                               | 1981-1996  |
| (Neij, 1999)                       | 8    | Denmark                                    | Denmark (turbine cost)                       | 1982-1997  |
| (IEA, 2000)                        | 32   | USA  | USA (COE)                                    | 1985-1994  |
| (IEA, 2000)                        | 18   | EU   | EU ( COE)                                    | 1980-1995  |
| (Taylor, Thornton et al., 2006)    | 14.5 | Global                                     | California (COE)                             | 1982 -2000 |
| (Neij, 2008)                       | 17   | Denmark                                    | Denmark (COE)                                | 1981-2000  |
| (Miketa and Schratzenholzer, 2004) | 10   | Global                                     | Global (ICC)                                 | 1971-1997  |
| (Junginger, Faaij et al., 2005)    | 19   | Global                                     | UK (ICC)                                     | 1992-2001  |
| (Junginger, Faaij et al., 2005)    | 15   | Global                                     | Spain (ICC)                                  | 1990-2001  |
| (Klaassen, Miketa et al., 2005)    | 5    |  | Germany, Denmark, UK (ICC))                  | 1986-2000  |
| (Kobos, Erickson et al., 2006)     | 14   | Global                                     | Global (ICC)                                 | 1981-1997  |
| (Jamasb and Kohler, 2007)          | 13   | Global                                     | Global (ICC)                                 | 1980-1998  |
| (Soderholm and Sundqvist, 2007)    | 5    | Germany, Denmark, UK                       | Germany, Denmark, UK (ICC)                   | 1986-2000  |
| (Kahouli-Brahmi, 2009)             | 17   | Global                                     | Global (ICC)                                 | 1979-1997- |
| (Nemet, 2009)                      | 11   | Global                                     | California (ICC)                             | 1981 -2004 |
| (Ek and Söderholm, 2010)           | 17   | Global                                     | Germany, Denmark, Spain, Sweden and UK (ICC) | 1985-2002  |
| (Wiser and Bolinger, 2010)         | 9.   | Global                                     | USA (ICC)                                    | 1982-2009  |

**Table 3.4 Wind energy extensive learning rates Junginger et al., 2010; Green-X, 2012; IPCC, 2012)**

The majority of the estimated learning rates are based on the investment costs, the installed capital costs (ICC) and a few on the cost of energy (COE). The latter have relatively higher learning rates. A possible explanation is that the COE cost estimate, in addition to investment costs, are also dependent on the performance of the wind energy converters which imply more opportunities of learning.

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## Offshore Wind

Offshore wind technology is still not yet as established as onshore wind on the market and requires further RD&D to enhance technology components and bring down technology costs. The next few years will determine the future success of this technology especially in countries such as the UK, China and Germany. The engineering based learning curve analysis of global offshore windfarms carried out by Junginger (2004) complemented with engineering assessments synthesised the cost reduction potential under different growth scenarios and concluded that, investment costs of offshore wind farms may decline by about 25-39% by 2020.

As it is still in the early stages of development, studies into the construction of offshore energy learning curve analysis are limited. A number of studies however, make use of learning curve analysis in interpreting the technological progression of offshore drawing a parallel with the more established onshore sector. Offshore wind benefits from the experience gained in onshore and when a system approach to learning approach is taken (see Section 3.2.1.1), the turbines for both technologies are nearly similar, learning rates of onshore are normally used for offshore turbines. Although the costs of offshore are still high compared to onshore, when the two are compared at 100 MW installed capacity, offshore wind has much lower specific investment costs as compared to onshore at that stage in the early 1980s (Junginger, Van Sark et al., 2010).

## Solar PV

PV has been established in a number of niche markets for years (Gross, Leach et al., 2003; Junginger, Van Sark et al., 2010). In terms of cost reduction, PV is the most impressive from several hundred €/Wp<sup>1</sup> to the present 4-5 €/Wp but it still has a long way to go before it reaches the investment cost levels similar to fossil fuel based technologies (Junginger, Van Sark et al., 2010). From 2000 to 2011, driven by strong policy support, solar PV was the fastest-growing renewable energy technology worldwide with an average annual capacity growth above 40% in this period.

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<sup>1</sup> Watt peak- The peak power rating of a solar PV module

Growth, however, has still been concentrated in only a few markets in countries such as Germany, Italy, the United States and Japan. The success of the technology will be highly enhanced if regions with good solar potential in Africa and parts of Asia add significant capacity.

The cost of PV has declined by a factor of 100 over the past four decades, more than any other energy technology. This cost trajectory appears to very closely fit a learning curve, in which a power law is used to relate costs to cumulative experience in production (Nemet and Husmann, 2012). Consequently, this technology has the most documented learning curves for renewable energy technologies spanning from the 1970s (Nemet, 2009; Junginger, Van Sark et al., 2010).

### **Other Renewable Technologies**

Concentrated solar thermal power has been in existence for many years, but there are very few learning curve studies due to a lack of historical data and a limited number of installations. Cost estimates in the medium to long term used in learning curves gave progress ratios in the range of 80% (Junginger, Van Sark et al., 2010). Bioenergy is the largest source of renewable energy, but it is mainly used for non commercial use in developing countries. For electricity production various forms of energy conversion of bioenergy exist, but they differ significantly from other renewable energy technologies in that they need fuel. For that reason amongst many, learning curves analysis is limited. The application of learning curves for marine energy is also limited because of their relatively early stage of development and the need for design consensus for the technology. However, marine energy technology assessments stand to benefit from learning curve methods developed from the relatively mature wind energy (Mukora, Mueller et al., 2008).

Table 3.5 gives a summary of the learning rates for the main energy technologies.

| Technology                         | Timeframe | PR (%) |
|------------------------------------|-----------|--------|
| Solar PV                           | 1970-2006 | 20     |
|                                    | 2002-2006 | 0      |
| Onshore Wind                       | 1990-2004 | 15     |
| Offshore Wind                      | 1990-2001 | 10     |
|                                    | 2002-2007 | -13    |
|                                    |           | 15-19  |
| Pulverised coal-fired power plants | 1942-1997 | 8      |
| Combine<br>Cycle Gas Turbine       | 1975-1990 | <0     |
|                                    | 1990-1997 | 25     |

**Table 3.5 Average Learning Rates (LR) for different energy technologies (Junginger, Van Sark et al., 2010)**

There is an observation that although conventional fossil fuel based technologies have reached maturity, they continue to learn and reduce costs in some areas, and this needs to be factored into energy modelling scenarios (Junginger, Lako et al., 2008).

The progress ratio of greater than 100% (negative learning rate) observed in the early stages of development of Natural Gas Combined Cycle (NGCC) can be attributed to increasing costs (see Section 2.3.3). However between 1992 and 1997 the costs reduced, resulting in a positive learning with a progress ratio of 75%.

## 3.5 Discussion

### 3.5.1 Learning Curve Methods

Learning curves in their classical form as applied to energy technologies have been used in an aggregate form, relating total costs or prices to experience. Moreover, there are suggestions, but no definite answers, whether or not the learning curve approach could be used for assessments when radical changes in the technology design (new types of PV, turbines etc) are introduced.

There is agreement in published literature that the learning curve approach in its aggregate nature has significant limitations when used for emerging energy technology assessments. Innovation is a cornerstone to the establishment of technologies relatively new to the market and with it comes change and possible

disruption to experience. The goal for early stage technologies is to control the short-term costs and to identify the key factors in long term cost developments.

Learning curves have been constructed using different methods resulting in variabilities in the learning rates published for energy technologies. Data and the purpose of the study have a great bearing on the choice of approaches to assessment. The relevancy of learning rates is improved if the timeframe of analysis is taken into account due to the possibilities of disruptions to cost reduction that might have a significant impact on the development cost of technologies.

Global assessments have the advantage of taking into account spillover effect, which might have more significance to long term energy systems modelling. On the other hand local assessments are more relevant for short term assessments that can capture technical changes necessary for early stage technologies. As the two approaches both have advantages it might be worthy considering the possibility of using of both local and global data for integrated models for detailed and aggregated analyses respectively.

Data availability for constructing learning curve models is a challenge for early stage technologies without significant historical data. Local data from the private sector have high confidentiality levels thus difficult to get and use. This is more pronounced for necessary cost data than the more available price data. However, price is dependent on technology maturity and other market related factors such as market stimulation and market diffusion. It is agreed that these cause variabilities in the relationship between cost and data in the early stages before the technology stabilises on the market. It is interesting to note that market factors continue to have an impact on price during all stages of technology development. Disruptions on the market can also result in changes in the assumed constant relationship between cost and price when the technology stabilises on the market. The scarcity of preferred cost data necessitates the development of engineering based methods to derive or estimate cost data.

### **3.5.2 Learning Effects and Other Sources of Cost Reduction**

The impact of R&D, technology design, manufacturing improvements, and scaling effects are better understood if they are isolated and analysed not only in the short term, but also in the long term context. The isolation of cost drivers can assist in the recognition of their contribution to the classical learning curve.

The suitability of learning curves for assessments when technologies experience radical change in addition to the incremental changes is still being questioned in research circles. However, there is agreement that the use of complementary methods has improved the ability to isolate some of the sources of cost reduction, and to model short term impacts. Whether the combination of this short term modelling and the learning curve approach results in the use of two or more separate learning curves or step changes in one learning curve, or whether they are insignificant in the long run, still remains to be investigated. Moreover, a number of published studies on complimentary methods are based on qualitative engineering assessment methods, based on expert judgements for isolating sources of cost reduction, as opposed to quantitative engineering methods.

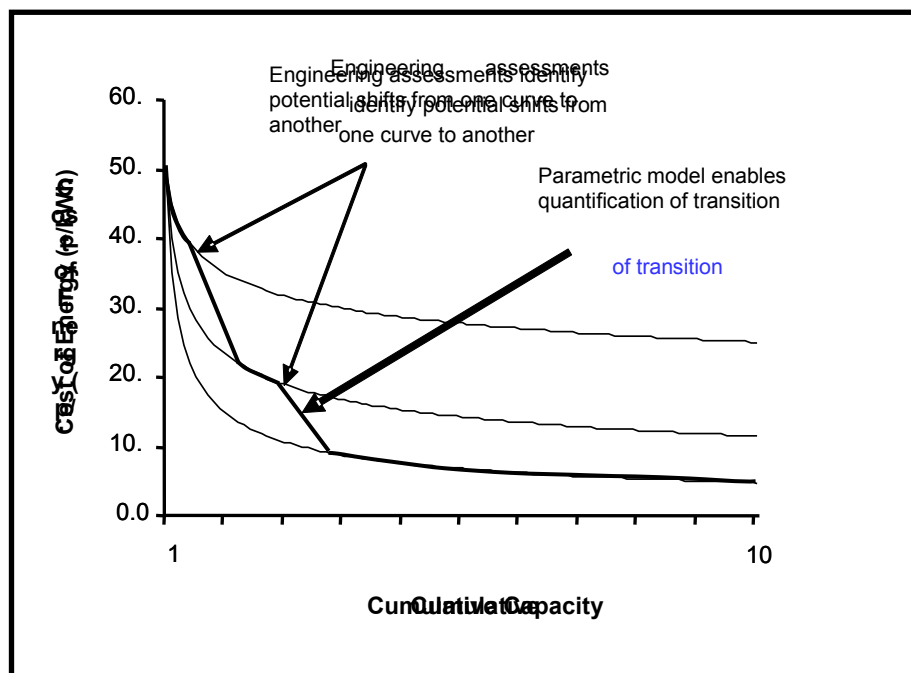
The isolation of factors and integration into learning curve methodologies provides valuable insights into emerging energy technology cost assessments. However the combination of methods result in complicated models that require improved data methods, as can be seen with the case of the two factor learning curve (2FLC) which is not yet as established as the aggregated classical learning curve. Neij (2008) mentions that it is difficult to separate scaling effects from learning effects, as the two overlap depending on the type of scaling. The complexity of models does not deter the need for such models, but calls for improved data methods that are step towards a representation of total cost reduction.

For a given technology, detailed engineering costing methods can be pivotal in the assessment of a reference technology component and overall cost data where it is limited. In addition, disaggregating a reference technology device into components allows analysis and quantification of the technical barriers and the technical improvements required to overcome these barriers. Design alternatives and



improvements can bring about change that overcomes limits to current configurations. It is necessary to investigate the use of engineering assessment of a technology in the process of identification and quantification of historical or anticipated future disruptions or alternatives within the technology brought about by innovation.

The detailed costing of a reference baseline technology is resource consuming. And further assessment of alternative concepts might be more demanding and result in complex models. The mathematically based parametric modelling can allow the projection of costs and other assessment parameters from the detailed engineering assessments to allow for any conceptual changes of components. The resulting cost models for different concepts have the potential to assist in quantifying relative cost reductions associated with technical improvements. Integration of such data with the learning curve may result in a model for emerging energy technologies similar to that suggested by Linton and Walsh (2004) for emerging process technologies and is worthy of investigation. Figure 3.4 shows a possible learning curve adapted from Figure 3.2 which might be obtained through the use of engineering assessments and parametric modelling.



**Figure 3.4** Illustration of learning curves for emerging technologies based on an integrated model

Typical changes are unlikely to be as radical as portrayed in Figure 3.2 (Linton and Walsh, 2004) but might involve a more gradual transition as suggested in Figure 3.4.

Discontinuities, whether gradual or radical, are bound to exist in the emerging energy technology learning curves, and with improved progress of emerging low carbon technologies, and related policy support mechanisms, it is important to examine the prospects of significant discontinuities in the learning curve in some detail.

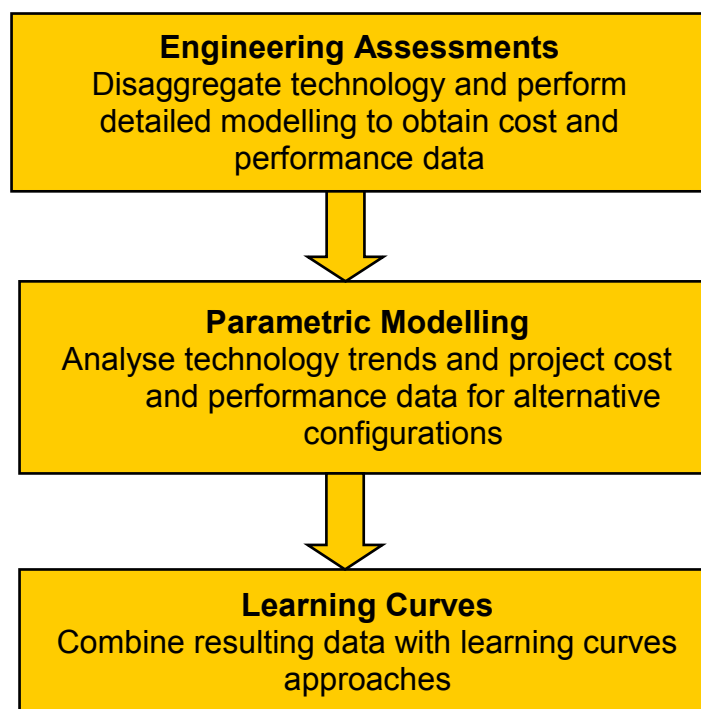
### 3.6 Proposed Approach to Assessments

It is proposed that modelling methods are developed for emerging energy technologies by initially using one specific technology, onshore wind. This is a clean electricity technology that is relatively well developed and can be categorised together with other technologies—offshore wind, tidal and wave energy technologies. The relative availability of data compared to other technologies makes it attractive to use for developing assessment methods.

Data collection is important and influences the type of learning curve as well as the quality of results, but it is time consuming. General global data for modelling work and validation purposes can be sourced from previous studies. Other sources include international energy institutions, such as the International Energy Agency (IEA) and Global Wind Energy Council (GWEC), country specific institutions, such as RenewableUK and the German Wind Energy Association (BWE), and relevant research organisations that maintain databases. These are mostly government funded and hence most of their information is publicly available.

As there is no obvious readily available source for relevant cost data, this will be estimated and derived using detailed engineering assessments mainly based on the Sunderland model (Harrison, Hau et al., 2000). Suitable cost models will be developed for wind turbines, as well as other technology cost centres, in an approach similar to that suggested for global offshore wind farms by Junginger (2005). Where data is limited, analogous engineering approaches will be used to derive data from previous studies.

In summary, the work is to be carried out in three stages. Firstly, detailed modelling will be performed to obtain much needed cost data for wind energy technology. Then in the second stage, parametric modelling methods are used to extrapolate cost data for alternatives concepts. Finally, the results of the two stages will be integrated into the learning curve assessments for wind energy technology. The integrated model proposed here will initially be developed for wind energy, a relatively well-established technology. It is beneficial to analyse how such a model could then be transferred to relatively immature technologies such as offshore wind and possibly marine energy. The process is summarised in Figure 3.5.



**Figure 3.5 Summary of proposed process of development of improved assessment methods**

### **3.7 Conclusion**

The chapter discussed the application of learning curves to energy technologies by firstly looking at the important factors in developing learning curves. Secondly it went on to review literature on specific studies where learning curves in their simple or improved form, through the use of complementary methods based on engineering assessment, parametric modelling and other related methods, were discussed. There has been considerable effort in a few studies to use other methods to improve learning curve methods and data, but there is still a need to further develop better suited methods for emerging energy technologies. It is important to investigate the integration of data from complementary methods into learning curves so as to improve their application to emerging technologies.

The development of such methods necessitates the use of a specific technology with reliable historical data, such as onshore wind. Learning curves of some emerging energy technologies were briefly discussed giving typical learning rates or progress ratios published in the literature. Onshore wind energy technology is relatively more

mature compared to other emerging low carbon electricity generation technologies and thus was chosen as the case study for developing improved methods of assessment that integrate learning curves and engineering assessments proposed Section 3.6. An overview of onshore wind technology and its technological trends is given in the next chapter.

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## 4 Onshore Wind Energy Technology Trends

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### 4.1 Introduction

This chapter introduces wind energy, the chosen technology for the main case study for this thesis. It focuses on the main components of the wind turbine and technological and cost trends. Wind energy technology is a low carbon renewable supply technology that has been well established on the market and has a relatively abundant data available for analysis. However, wind energy like other renewable technology still needs to be optimised economically so it competes with conventional energy technologies. Generally, there has been design consensus on the overall wind turbine technology, but there is still potential for cost reductions with technological development of the turbine subsystems and components. Recent trends have seen upscaling of the turbine to multi-MW levels and a move to offshore as well as other configuration changes to reduce costs and improve on performance.

Onshore wind energy technology can be classified as mechanical renewable energy supply technologies together with other technologies such as offshore wind, wave and tidal energy. These technologies are mainly based on the principle of converting mechanical energy of air or water to electricity. Onshore wind is the most well developed technology in that category and its analysis could benefit offshore and marine technologies, which are in earlier stages of development, as well as other emerging energy technologies in general. Although multiple types of learning curves for wind energy technology have been developed, their use has also been associated with limitations as discussed in Chapter 2. Engineering assessment methods have been used for wind energy technology assessment, but evidence of the use of integrated methods is limited. Consequently this technology was chosen as the one to use to develop methods to improve assessment of emerging energy technologies. This chapter introduces wind energy technology, its history and current status.

Section 4.2 gives an overview of the current status of wind energy in the UK, Europe and world over. Section 4.3 describes the wind turbine system and its major subsystems and components. Section 4.4 analyses technological developments of wind turbines focusing on upscaling and major conceptual changes. Section 4.5 briefly discusses wind energy cost developments over the years followed by a discussion in Section 4.6. Finally, section 4.7 concludes the chapter suggesting the need for a detailed cost analysis of the wind turbine and other cost of energy (COE) cost centres.

## **4.2 Wind Energy Overview**

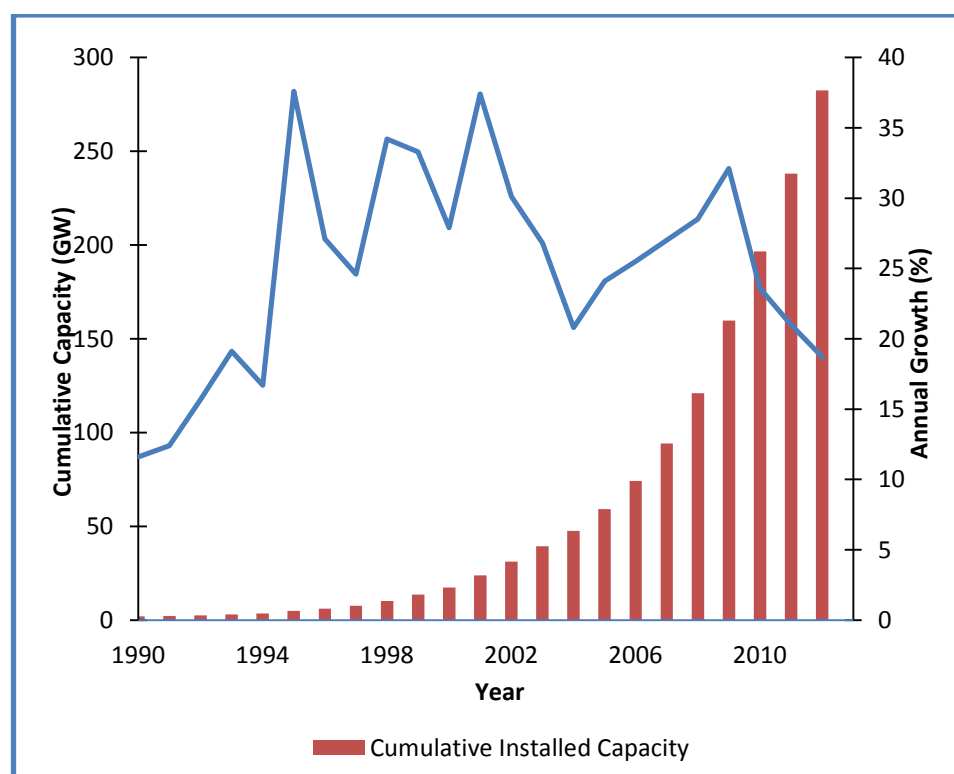
Wind energy technology is one of the oldest forms of renewable energy technology. It is based on the principle of converting kinetic energy of moving air to, as in the past, mechanical energy for grinding or water pumping, and more recently to electrical energy via a generator (Junginger, Van Sark et al., 2010). Windmills, for mechanical purposes were invented centuries ago and still exist in some parts of the world where they are used for pumping water. Attempts to design and manufacture wind energy conversion systems (WECS) for electricity production were as early as the end of the 19<sup>th</sup> century (Boyle, 2004; Hau, 2006). Large scale electricity production from wind started in Denmark and USA in the late 1970s in response to the oil crisis (Junginger, Van Sark et al., 2010). Wind Energy technology has become a mainstream source of electricity generation around the world in efforts to cut greenhouse gas emissions and solve some of energy sector challenges (Lantz, Wiser et al., 2012b). Its future is dependent on continued cost reduction and competitiveness with conventional sources.

### **4.2.1 Global Capacity and Growth**

Historically, wind turbines have been installed onshore with the first commercial turbines located strategically in areas of high winds. As these areas became exploited the move offshore with greater abundance of wind resources became inevitable. Onshore wind and offshore wind energy technologies are at different levels of maturity with onshore more established. However, some statistics do not differentiate between offshore and onshore. Currently, as offshore continues to be developed,

onshore installations make up the significant share of the installed GW capacity, estimated at 98% in 2012 (GWEC, 2013). In developing assessment methods for wind energy, this study focuses on onshore wind energy and the possibility of combined statistics for wind energy cumulative capacity is taken into consideration when such data is used.

Worldwide wind energy installed capacity reached 254 GW<sup>2</sup> by end of June 2012 of which 16.5 GW was installed in the first half of 2012 a 2% growth reduction compared to the 18.4 GW installed in the same period in 2011 (40 GW for the whole year in 2011). Figure 4.1 shows the trend for global installations since 1990.



**Figure 4.1 Global cumulative capacity and annual capacity growth of onshore wind energy**

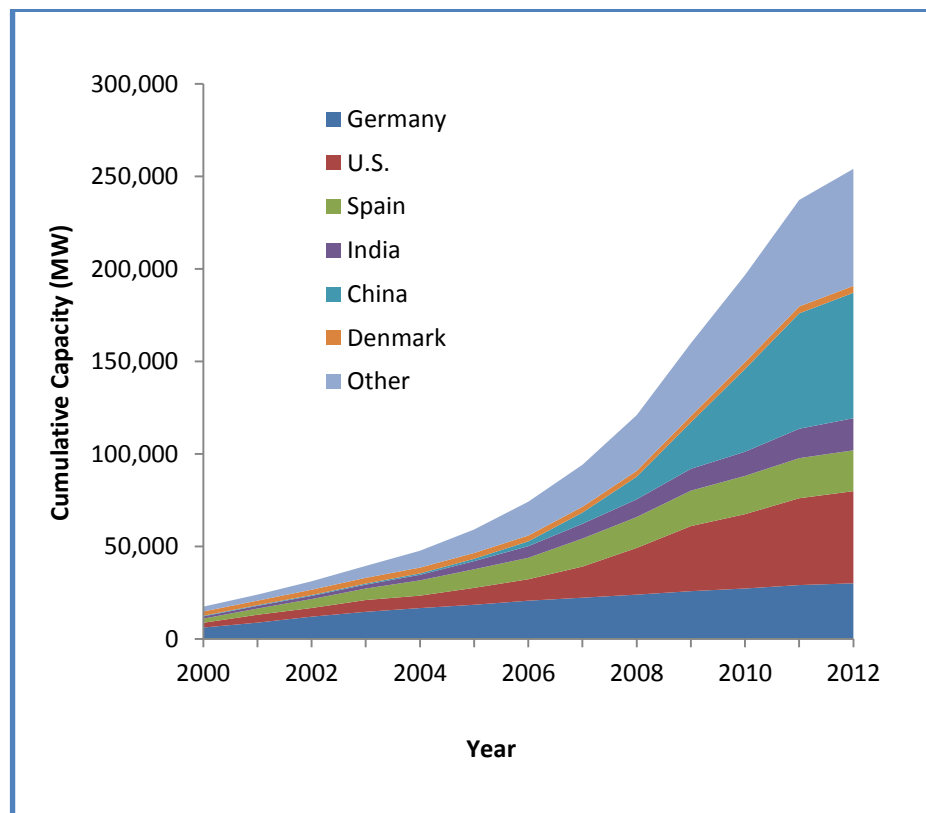
In 2008 wind power provided approximately 1.3% of global electricity in TWh and by the end of 2009 wind power was capable of meeting approximately 1.8% of

<sup>2</sup> Global Wind Energy Council (GWEC) reported a global cumulative installed capacity of 282 GW at the end of year 2012 with the top 10 countries accounting for 85.9% GWEC. (2013). "Global Wind Energy Council-Global Statistics." Retrieved February 2013, from <http://www.gwec.net/>.



global electricity demand and this rose to 2.2% translating to 440TWh of electricity (RenewableEnergyWorld.com, 2009; IPCC, 2012). It is predicted that this could grow to in excess of 20% by 2050 if ambitious efforts are made to reduce greenhouse gas (GHG) emissions and to address the other barriers to increased wind energy deployment (IPCC, 2012). In the short term predictions in 2008 were 3.35% by 2013 and 8% by 2018 (RenewableEnergyWorld.com, 2009).

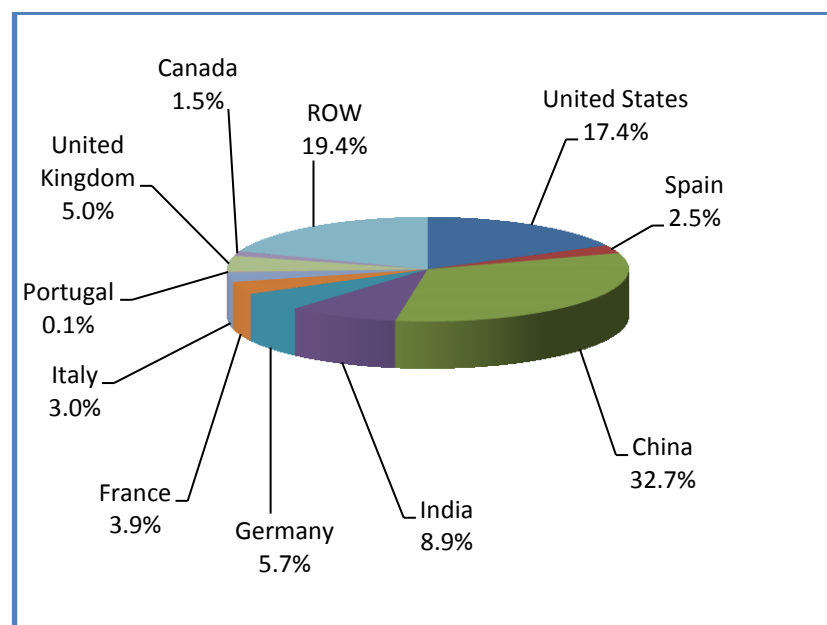
In the past 2 decades wind energy growth has been rapid globally, and is now established in over 80 countries, but a few countries dominate in terms of installations (Jaeger-Waldau, Szabo et al., 2011). Currently China, USA, Germany, Spain and India lead global installations (Wiser and Bolinger, 2010). Figure 4.2 shows the trends of cumulative installed capacity for the major countries.



**Figure 4.2** Wind Energy Installed Capacity of main countries for period 1990 to 2012. Sources (Wiser and Bolinger, 2009; Wiser and Bolinger, 2010; Wiser and Bolinger, 2011; EWEA, 2012; GWEC, 2012; EWEA, 2013)

From 2009, China emerged as the largest wind power market in terms of installed capacity driven primarily by the need to increase the energy supply for this emerging economy. In 2010, taking over from USA, the country became the leader in terms of installed capacity as it added 18 928 MW in 2010 (WWEA, 2011). China's growth rate in 2010 was 73% compared to the global growth rate of 24%. Though the country continues to lead with an overall 67.7 GW by mid 2012, recently the growth rate has seen a reduction accounting for 32% of world market for new turbines compared to 43% in 2012. It is forecast that China will continue to lead but at a lower rate of growth (WWEA, 2012; WWEA, 2012b).

Figure 4.3 shows the major countries rankings in terms of new installations for the year 2012.



**Figure 4.3** International rankings of wind power capacity-added capacity in 2012 (WWEA, 2012b; EWEA, 2013).

Wind energy plays an important role in the European 2020 ambitious targets (EWEA, 2012). Wind energy installed capacity reached 106 GW in 2012 after a steady increase for nearly 20 years. In 2012, 11,895 MW was added compared to 814 MW added in 1995 (EWEA, 2012; EWEA, 2013). It is expected that installed capacity in Europe by 2020 will increase to 230GW installed wind capacity in

Europe: 190 GW onshore and 40 GW offshore (EWEA, 2010). This translates to an increase from 163 TWh (2009) to 580 TWh (2020) in electricity production.

Most of growth in Europe can be attributed to Germany and Spain, UK, Italy and Denmark continuing its steady progress (EWEA, 2010; EWEA, 2013). Furthermore, wind is almost completely unexploited in the new Member States. In Europe, as long as wind remains a small fraction (less than 10%) of total electricity generation, there is no problem integrating wind energy into an electrical grid. Beyond this level of penetration, problems with reliability and stability of power supply may occur and research efforts are needed to solve or at least reduce these problems (IEA, 2012; Hansen, Cutululis et al., 2009). A European supergrid has been proposed by extending and upgrading the existing grid (EWEA, 2010; EWEA, 2012).

In the UK, onshore wind is the most established renewable technology, with a strong history and is recognised as a key component of the UK renewables mix. (Arup, 2011). According to the Department of Energy & Climate Change (DECC), the UK already has more offshore wind capacity than any other country in the world and it is anticipated it will be a leader in installations (DECC, 2013; DECC, 2013b). Onshore and offshore wind generation can make a significant contribution to the UK's renewable energy targets and aspirations given the UK's substantial wind resource with a feasible resource potential in the range 20 to 30 GW (Arup, 2011) and the relatively advanced nature of wind generation technology. The UK is one of a small number of countries to have reached 5 GW of wind power (onshore and offshore), and is number one in the world for offshore wind power generation, having overtaken Denmark in 2008 (DECC, 2013; DECC, 2013b). In 2011, electricity production from wind reached 11.1% in the last quarter for the year giving hope that an annual target of 10% of electricity from wind can be reached in the near future (DECC, 2013; DECC, 2013b).

#### **4.2.2 Offshore Wind Overview**

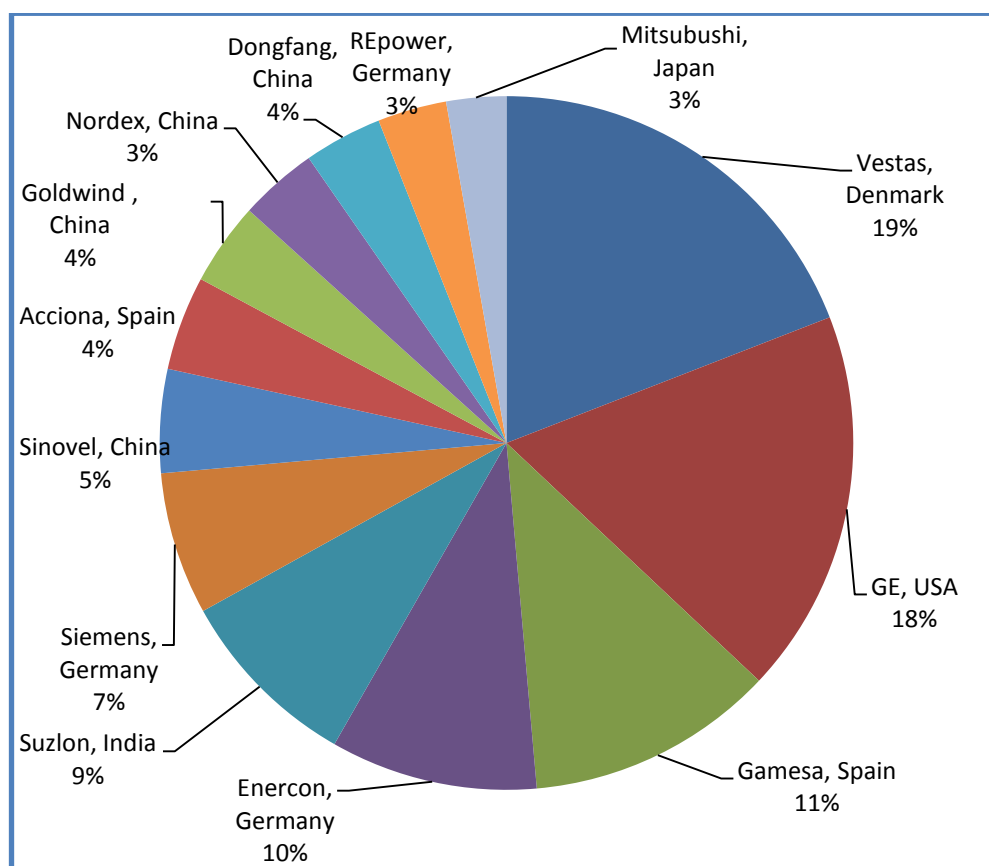
Offshore wind is a relatively new technology, currently more costly than onshore but it is anticipated that costs will reduce and the technology will advance, helping offshore wind to be more efficient and cost competitive in the near term (Junginger,

Faaij et al., 2004; Greenacre, Gross et al., 2010; GWEC, 2013). Currently offshore wind turbine technology is basically similar to onshore, with the major differences being: foundations, installation, and access and corrosion control.

Offshore wind energy has an enormous resource potential and could assist in combating climate change and in meeting global energy demands, particularly in Europe and America where there is potential or surpluses if fully exploited (GWEC, 2013). The technology plays an important role in contributing to Europe's binding target to source 20% of final energy consumption from renewables, and China has set itself a target of 30 GW of installations off its coast by 2020. United States has many projects under development, but there was no offshore wind power installed yet as of the end of 2012. More than 90% of the world's offshore wind power is currently installed off northern Europe, in the North, Baltic and Irish Seas, and the English Channel. Most of the rest is in two 'demonstration' projects off China's east coast (GWEC, 2013).

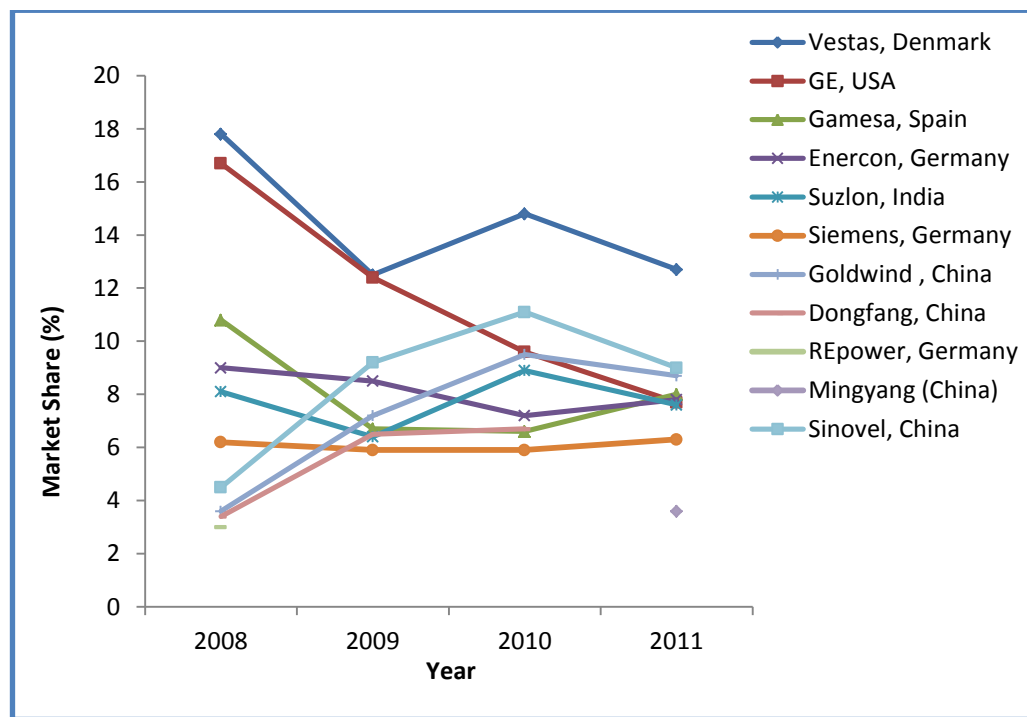
#### **4.2.3 Wind Turbine Manufacturers**

The majority of turbines are produced by a few companies referred to as original equipment manufacturers (OEMs). The top ten group of wind turbine suppliers account for a market share around 85% of total global supply (85% in 2008 and 86.4% in 2011) (BTM-Consult, 2009). Figure 4.4 represents the shares of the major OEMs in 2008.



**Figure 4.4 Global Original Equipment Manufacturers (OEM) market shares in 2008**

In the late 2000s Vestas and GE Energy were the then market leaders with a share of 19.8% and 18.6% respectively of the world supply market in 2008. However, over the past few years Chinese manufacturers have rapidly risen up to join the top ten taking over some of the traditional manufacturers, majority of which are European companies. Figure 4.5 illustrates the trend for the top ten manufacturers from 2008 to 2011.



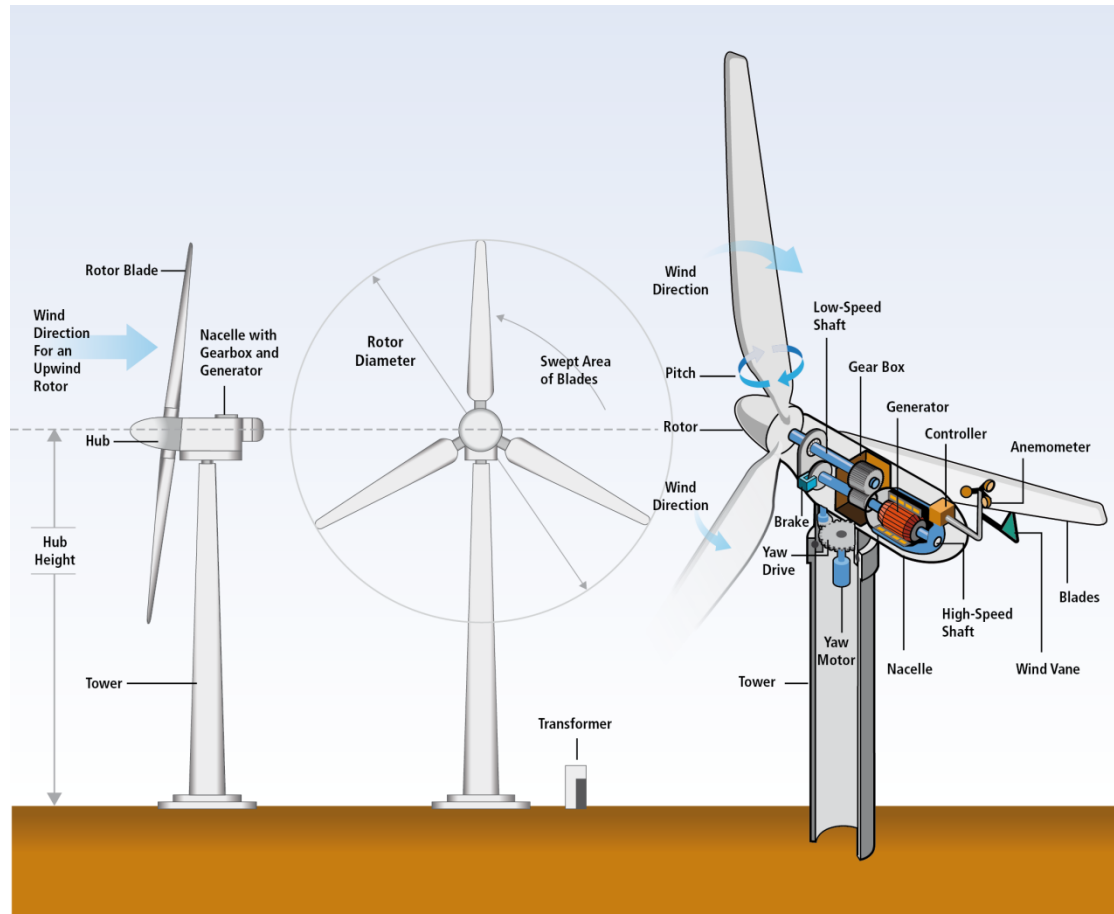
**Figure 4.5 OEM market shares 2008 to 2011 (BTM, MAKE and EER (<http://www.evwind> for 2011 data))**

As China emerged as a leader in wind turbine installations from the late 2000s, it created a market for the suppliers in the country thus increasing the global share of the manufacturers in that country. By 2011 Sinovel, a Chinese company had joined the top five manufacturers.

### 4.3 Wind Turbine Components

The wind turbine is a complex system with many components, but can be simplified and divided into a system of components or subsystems. Over the years since the conception of wind turbines various designs were proposed but converged in the 1980s and 1990s into a dominant design which is known as the “Danish concept”: 3 bladed, horizontal axis, upwind turbine driving an electrical generator through a speed increasing gearbox and mounted on a tower (DNV/Risø, 2002). The standard wind turbine is made up of 4 main sub-systems: the rotor, nacelle, drivetrain and tower.

The turbine also has other mechanical, electrical and electronics *ancillaries* such as brakes, couplings, cables, control systems, transformer and power electronics converters. These are mainly located in the nacelle as part of the drivetrain or at the bottom of the tower. Figure 4.6 is a representation of the major turbine components.



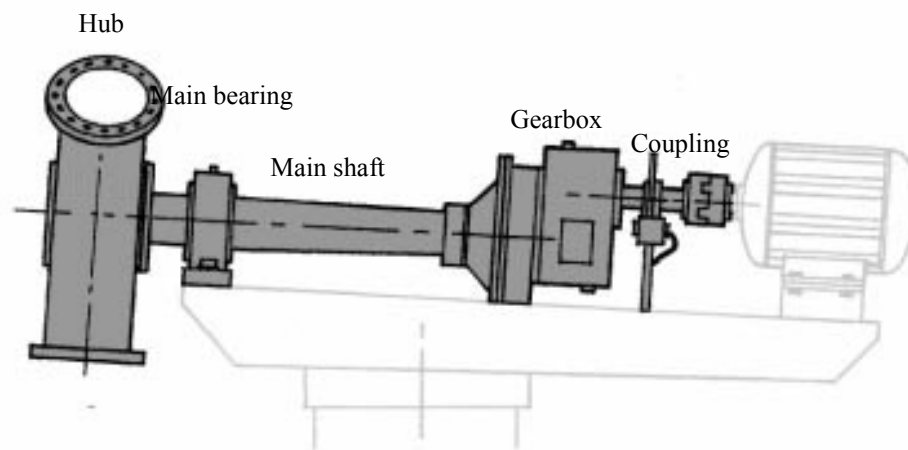
**Figure 4.6** Wind turbine subsystem arrangement Design by the National Renewable Energy Laboratory NREL (Lapre, 2009)

Wind turbine blades are designed to aerodynamically capture energy in the wind and convert its energy to low speed rotational mechanical energy. The majority of commercial turbines have three blades. Two bladed rotors have been developed, but suffer balancing technical issues and visual acceptability problems (Hau, 2006). Wind turbine blades are advanced in design, but labour intensive in the manufacturing process, because of processes like adding layers of glass fibre to blade moulds and finishing the edges of blades. It takes about one week to produce a blade (Rogowsky and Laney-Cummings, 2009). Blades on fixed speed and variable speed

turbines are pitched by hydraulic or electrical actuation, in order to provide control and power regulation. The pitch mechanism also has the function to brake the blade aerodynamically by increasing the pitch angle to the feathered position (Hau, 2006).

The hub is a fixture for attaching the blades to the shaft. It is part of the rotor with blades and the pitch mechanism; however, it is closely associated with the mechanical drivetrain in terms of function and structure. The rotor hub is one of the most highly stressed components of a wind turbine. It is cast because of its complex shape and the casting needs to be carefully designed to reduce metal fatigue (DNV/Risø, 2002). Hubs for MW turbines are mainly cast from spheroidal graphite iron to improve the fatigue inception stress. Compared to grey cast iron, spheroidal graphite iron has higher ductility, tensile strength, modulus of elasticity and resistance to elevated temperature oxidation.

Figure 4.7 shows how the hub is connected to the drivetrain, which consists of the shaft, gearbox and generator, with appropriate bearings and couplings. In the case of a direct drive machine there would be no gearbox and the hub and generator would be directly coupled.



**Figure 4.7** Typical drivetrain. Source – Bonus Turbines (Stiesdal, 1999)

The gearbox converts the low rotational speed, high torque from the rotor to high rotational speed and low torque necessary for the generation of electricity in conventional wind energy conversion systems (WECS). The majority of gears are



one of 2 distinct types: parallel (spur) and epicyclic (planetary). Parallel gears are heavy but inexpensive and useful for high speed and low torque applications whereas planetary gears are lightweight, compact and complex, and are mainly used for low speed and high torque applications. Typically, commercial turbines have 2 or 3 stages with most MW turbines gearboxes having 3 stages in a combination of and planetary gears for low speed end and spur gears for the high speed end.

In the region of 85% of all large wind turbines greater than 1MW use the doubly fed induction generator (DFIG) driven by a gearbox. The advantage of the DFIG over the more conventional squirrel cage induction generator (SCIG) is that the power converter rating for the DFIG is only 30% of the machine rating, as it is used in the rotor circuit to provide control for the turbine speed. In the DFIG, the stator is directly connected to the grid. In direct drive systems, the field wound (Enercon, 2012) or permanent magnet (Vensys, 2012) synchronous machine is the generator choice of manufacturers.

These are various mechanical equipment components necessary for the turbine especially for the drivetrain. The major components include couplings, brakes, cooling and lubrication equipment and air conditioning systems. The mechanical brake system is used as a backup system for the aerodynamic braking system or as a parking brake when the turbine is stopped for service. Hydraulic system provides high pressure fluid to the brakes and actuators and power to the yaw system in some designs.

Additional electrical equipment for the turbine equipment includes electrical cables, switch gear, power factor correction capacitor banks, power converters for grid connection and step-up transformers. Control systems monitor the condition of the turbine, optimise the energy captured and provide power conditioning for grid connection. This equipment is normally located in the nacelle, but often the transformer is at the base of the turbine.

The nacelle houses the drivetrain equipment and has to be designed to carry the resulting loads. The subsystem consists of the bedplate (mainframe), the nacelle cladding (covering) and the yaw mechanism.

The yaw denotes the rotation of the turbine about the vertical tower axis. The mechanism provides a system to position the turbine and keep the rotor axis aligned with the wind. The system has a bearing that supports the nacelle and is located between the rotating nacelle and the stationary tower and transmits loads from the nacelle to the tower. It has a yaw drive that is responsible for the yaw motion.

The tower of a turbine supports the nacelle and the rotor and provides the necessary elevation to keep the turbine off the ground and bring it to a height where the wind resource is. Raising a wind turbine high above the ground increases its power output because at higher heights air flows are less turbulent, stronger, and more reliable - particularly at low wind speeds. Towers are typically made of steel, though concrete are used for the largest turbines, for example, the 7.5 MW Enercon direct drive turbine. Most commercial turbines use tubular towers, though a significant number are lattice for exceptionally tall towers, for example, Fuhrlander turbines.

#### **4.3.1 Wind Turbine Performance**

The energy extracted from the wind is dependent on the turbine and the way it interacts with the resource at the site where it is installed. Individual turbines are rated according to the generator nameplate capacity in MW. The total energy yield of the turbine over a given time period expressed as MWh is of more relevance for turbine performance assessment. The turbine operates at a wide range of speeds and therefore it will not produce energy at rated capacity all the time. An important measure of performance, the capacity factor of a turbine is the measure of the energy produced as a ratio of the energy it would produce if the turbine operated continuously at rated power (Ffrench, Bonnett et al., 2005; Hau, 2006). Typical capacity factors in the UK are in the range 20-30% for onshore and 30-40% for offshore (Ffrench, Bonnett et al., 2005; BWEA, 2012a). Capacity factor can be increased at the expense of the total energy yield by reducing maximum generator output of a large rotor diameter turbine.

## **4.4 Technological Development**

Significant progress has been made in wind turbine technology since the advent of large scale commercial wind turbines in the 1980s. Sahin (2004) describes this progress as a continuous chain of incremental improvements based on experience. The major trend experienced for wind energy technology has been the gradual growth in size of the turbine. The upscaling of wind turbines to turbines of large diameters has led to higher towers resulting in increased wind capture leading to high electricity production. With these incremental size changes, a series of challenges related to mechanical loading and size increases and the need to continually reduce costs have resulted. This has necessitated further need for design changes and improvements and this coupled with a growing market has resulted in significantly radical concepts for some of the components and subsystems.

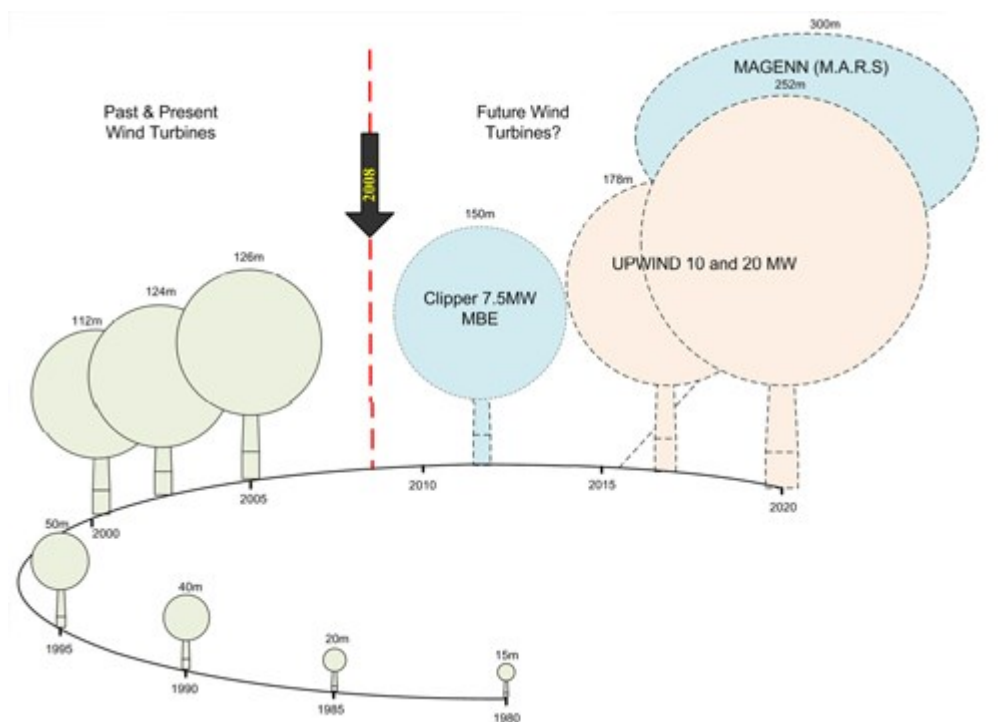
The move offshore where higher quality winds with faster speeds and lower shear exist has also been a major breakthrough in the development of wind energy technology. Though these two technologies have much similarities and offshore development has learnt a lot from onshore, the two are separate technologies with different technology pathways and will be treated as such. Generally, offshore turbines are designed with enhanced corrosion prevention measures and with ease of access and remote control.

The gradual upscaling of turbines will be discussed below first, followed by significant conceptual alternatives that have impacted onshore wind technology over the years.

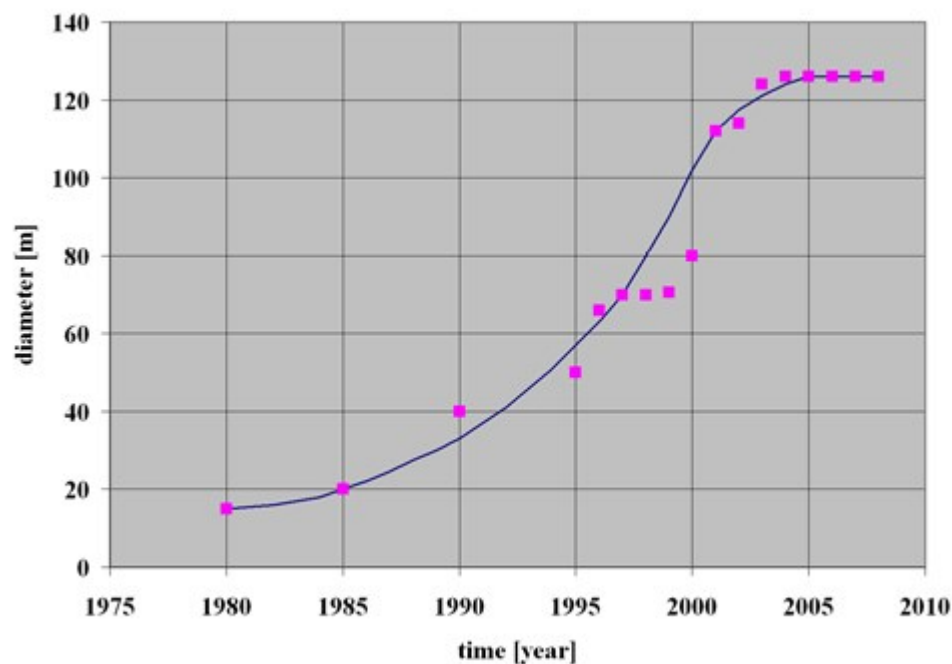
### **4.4.1 Upscaling**

The power that can be extracted by a wind turbine is directly proportional to the area swept by the blades meaning that the larger the blades, the more the resulting energy. In addition, larger turbines on high towers are exposed to faster and more productive winds with reduced disturbances. Consequently, globally, the average large wind turbine size has steadily increased over the years a diameter of around 15 m and power rating of 50 kW in 1980 (Ffrench, Bonnett et al., 2005) to large 126 m and 5-

7.5 MW turbines on the market which are mainly for offshore installations (Enercon, 2012). The average commercial turbine size is around 2.5 MW. As of the end of 2012, the largest operational wind turbine was the Enercon E-126 with a rated capacity of around 7.5 MW and research continues for even larger turbines (Polinder, Bang et al., 2007; UPWIND, 2012; WEM, 2012). Enercon's 7.5 MW turbine is one of the largest wind turbine type in the world and can generate about 20 GWh of electricity per year, which is enough to power 5,000 four-person-households (Knight, 2010). Figure 4.8 illustrates the growth in size from 1980 to 2008 and forecasts to 2020 of the turbines based on the largest turbine on the market and Figure 4.9 shows turbine gradual upscaling trend over time in terms of the rotor diameter.



**Figure 4.8** Turbine Diameter Growth with time (Gardner, Garrad et al., 2009)

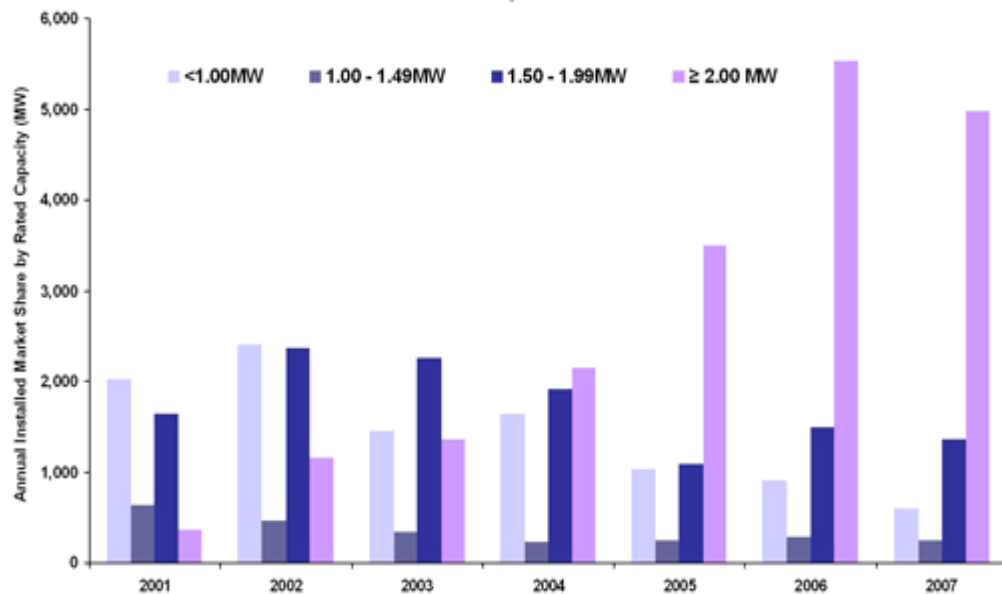


**Figure 4.9 Turbine diameter growth (Gardner, Garrad et al., 2009).**

As can be seen from the Figure 4.9 above there was a rapid growth in size from the early 1990s to mid 2000s. Thereafter there is decreased growth trend of the diameter of the largest turbines on the market from 2000 with no significant changes of the largest turbine diameter of 126m. Continued increase of the blade diameter has limitations and challenges in the design and manufacture of components including increased loads and transport challenges and limitations. As research continues to find solutions to such barriers, manufacturers such as Enercon and REpower have resorted to designing turbines with higher power ratings at the same diameter.

In Europe, turbines under 1 MW were the most proven designs and had their peak installation in 2004 (Pullen, Hays et al., 2009). Thereafter, the 1-1.5 MW turbine range became popular in some European markets responsible for 30% of all annual installations. The trend towards larger MW turbine has seen a decline in this turbine range. In particular, there was a major drop between 2004 and 2005 as leading suppliers concentrated on larger models development and serial production which involved specialising some of the plants for these large designs (Pullen, Hays et al., 2009). The 2 MW and larger units have become virtually the standard in Europe

since 2005 and in that year the range was responsible for 50% of the total installations in terms of installed capacity were. 2007 saw this range hit most by component shortages but the range continued to be the majority of installations globally (Pullen, Hays et al., 2009). Figure 4.10 illustrates the trend of the average wind turbines ranges between 2001 and 2007 in Europe.



**Figure 4.10 Average turbine size installations in Europe. (Pullen, Hays et al., 2009)**

The upscaling of turbines had the advantage that the setup of every new turbine class was based on past experiences, but also allowed a slow introduction of new technological developments, such as the application of pitch-regulation, the use of synchronous generators and the DFIG, the development and use of new materials for blades that grew larger and larger, development of power electronics, and the specialization of standard components from other industries for wind energy power, such as gear boxes, transformers and converters (Dale, Milborrow et al., 2004; Junginger, Faaij et al., 2005). Upscaled wind turbine development with improved performance and higher towers has led to increased wind capture and electricity production. Moreover, better wind resources estimation techniques enable improved wind turbine siting, resulting in increased yield.

Upscaling of wind turbines clearly is associated with challenges which had to be, and some still are yet to be overcome. It is difficult to determine the total impact of

increasing the rating or rotor diameter (Fingersh, 2006). Increases of parameters such as hub height or mass are not always linear with diameter increases. For a period up to mid 1990s the allowable mass of components was restricted by available cranes until manufacturers started producing cranes specially suited for wind farm installations (Gardner, Garrad et al., 2003). Therefore, upscaling to MW turbines did not result into just larger turbines but challenges associated with required design changes in the whole system. With forecasts to even larger turbines further design changes and assessment of these changes becomes of paramount importance.

## **4.4.2 Major Conceptual Changes**

### **4.4.2.1 Introduction**

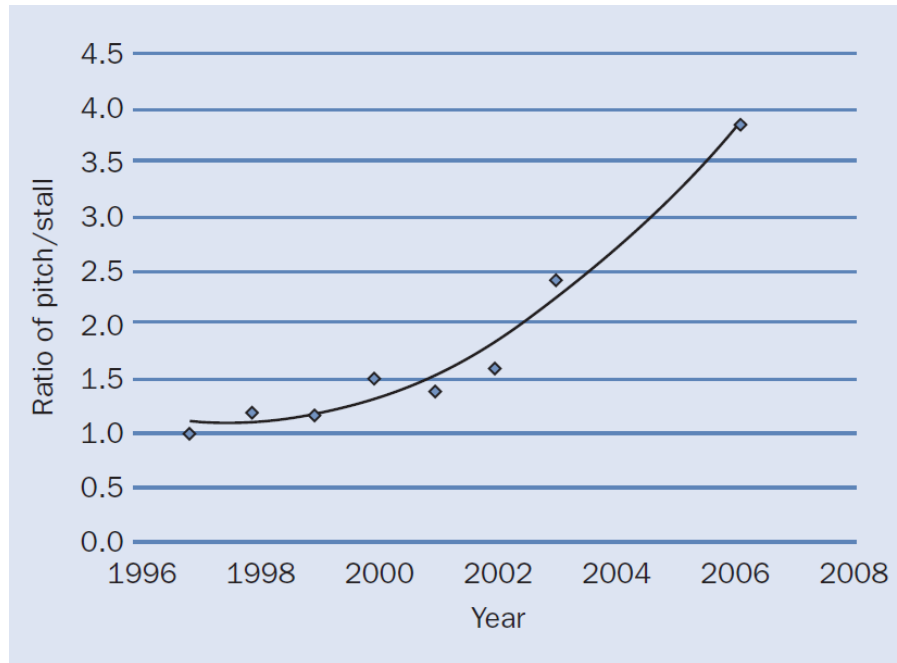
The ideal wind turbine system is not dictated by the technology only, but by a combination of technology and the economy and optimisation aims to achieve machines that deliver electricity at the lowest cost per unit of energy. Over the years as wind power technology developed manufacturers strived to optimise wind power for cost reduction and efficiency and reliability improvements, the following major factors became important:

- power control- stall or pitch
- speed control-fixed or variable
- drivetrain design -gearbox or no gear box and innovative generators

### **4.4.2.2 Power Control**

The main two systems for power control at high wind speeds are stall regulated systems and pitch regulated system. Stall-controlled turbines are carefully designed so that at high wind speeds turbulence is created and flow separates to prevent increases in power. In pitch control, the angle of the blades is mechanically adjusted to control power output at high wind speed with using hydraulic or electric actuators (Hau, 2006; Barthelmie, 2007). The cost of the two systems is quite similar, but pitch regulation potentially produces better power quality. For stall regulation, there is concern of stall induced vibrations. Pitch regulation is favoured over stall regulation

for large MW turbines mainly because of the advantage in terms of energy extraction and the improved control of power output to the grid (Barthelmie, 2007; Hansen and Hansen, 2007). Figure 4.11 shows the increase in market share of pitch regulated turbines compared to stall regulated.



**Figure 4.11 Ratio of pitch vs. stall regulated turbines on the market. Source Garrad Hassan in (Gardner, Garrad et al., 2009)**

#### 4.4.2.3 Speed Control

Wind turbines are run either at fixed speed or variable speed. In contrast to conventional power generation where input energy can be scheduled and regulated, wind energy is not a controllable resource, due to its intermittent and stochastic nature. Historically, most wind turbines operated at fixed rotational speeds, until the late 1990s when the trend turned towards variable speed for MW scale turbines (Polinder, Van Der Pijl et al., 2006; Gardner, Garrad et al., 2009). In fixed-speed operation the maximum coefficient of performance is only available at a particular wind speed. A low coefficient of performance is observed for all other wind speeds, which reduces the energy output below what might be expected from variable speed operation.



The majority of MW turbines on the market utilise a variable speed drivetrain. (Polinder, Van Der Pijl et al., 2006; Polinder, Bang et al., 2007b; Bang, Polinder et al., 2008). A higher output is realised by adjusting the turbine speed in relation to the wind speed so that turbine aerodynamic efficiency is being optimised. Variable speed is more grid friendly, quieter and its operation is more flexible in terms of energy capture, but requires sophisticated power electronics which are expensive (Marsh, 2004; Barthelmie, 2007). Another speed control concept based on limited variable speed control has been used by some turbine manufacturers, but the variable speed concept using a power converter remains the most dominant concept (Hansen and Hansen, 2007; Li and Chen, 2008).

#### **4.4.2.4 Drivetrain Design**

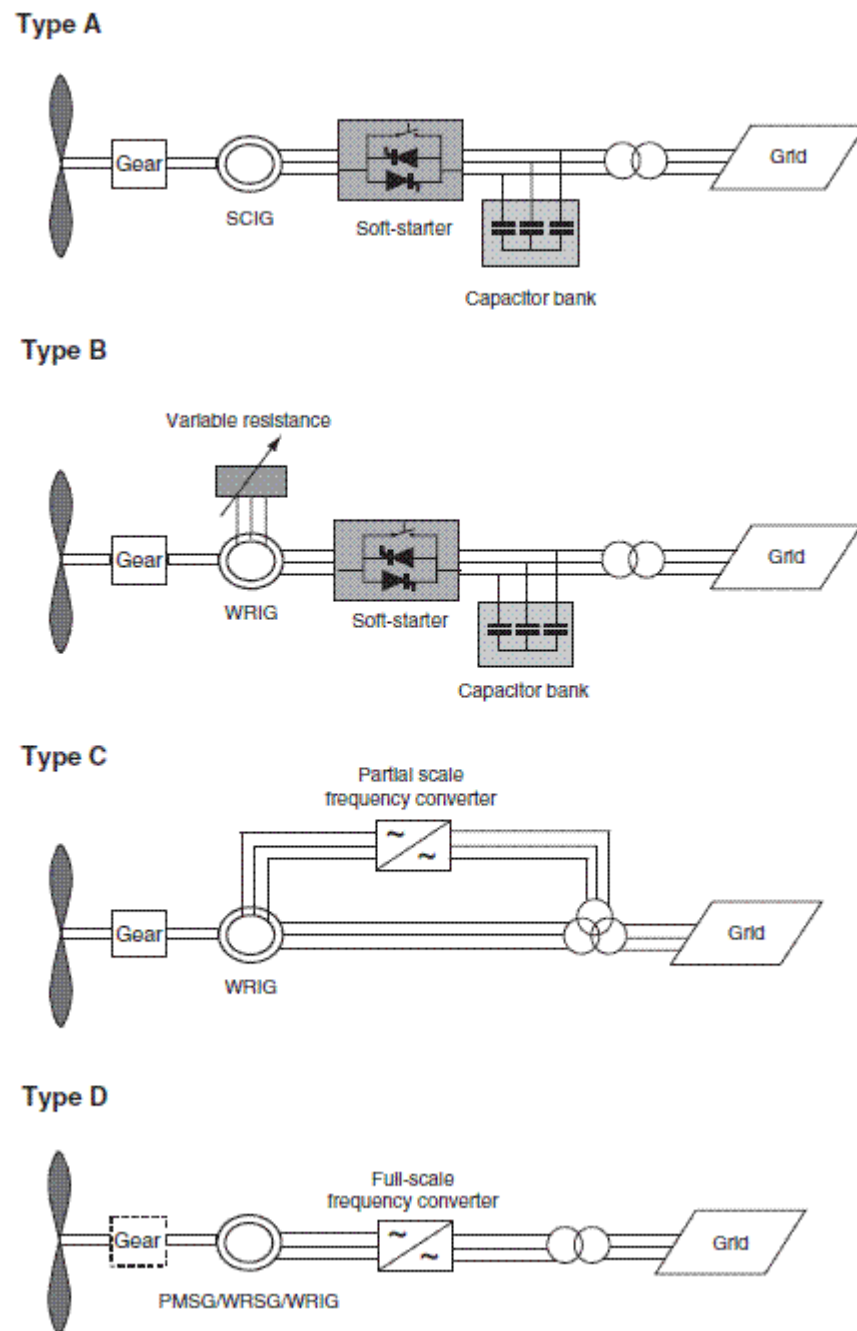
The early Danish concept turbine drivetrain was a 3 stage gearbox with a squirrel cage induction generator. A number of drivetrain alternatives have evolved through the years. Since the inception of wind at large scale in the 1970s and the rapid development in the 1990s, the drivetrain is the subsystem that has experienced the greatest amount of incremental as well as radical changes to its components (Bywaters, John et al., 2005; Spooner, Gordon et al., 2005; Li and Chen, 2008).

Since the early 1990s, some wind turbine manufacturers used gearless drivetrain systems with the so-called direct-drive generators, mainly to reduce failures in gearboxes and to reduce maintenance costs (Spooner, Gordon et al., 2005; Polinder, Van Der Pijl et al., 2006). A power electronic converter for the full-rated power is then necessary for the grid connection. The low-speed high-torque generators and fully rated converters for these wind turbines are expensive. Some manufacturers, most notably Enercon, favour the gearless direct drive turbine with a wound rotor synchronous generator and full rated power inverter to solve the problem of conversion of power to grid frequency especially at low rotor speeds. One disadvantage of the direct-drive system is the heavy towerhead mass (de Vries 2004), although this is reduced by the use of permanent magnets in the more innovative concepts and redesigning other components like the bearings.

The most popular drivetrain system currently is the gearbox driven double fed induction generator (DFIG), also called the wound rotor induction generator (WRIG). This provides almost all the benefits of full-range variable speed drives, but only a proportion, perhaps one-third, of the power passes through the converter (Gardner, Garrad et al., 2009). The majority of MW turbines on the market are based on this concept.

There are other alternative drivetrain concepts existing on the market designed to reduce the towerhead mass (mass of all the components above the tower), for example, the Multibrid 5 MW turbine which uses a multistage gearbox with fast-running generator. Gearboxes until recently used standard components but the design drive to reduce weight and loads on large turbines has driven production to lighter compact gearboxes specifically designed for wind turbines. Other drivetrain concepts include the limited variable and the medium speed system with 1 stage gearbox (Poore and Lettenmaier, 2002; Bywaters, John et al., 2005).

Hansen and Hansen (2007) carried out a study to analyse the market penetration of the major turbine concepts based on the drivetrain design. The analysis was mainly based on an investigation of the market penetration of the different wind turbine concepts by BTM Consults Aps for about 168 wind turbine types by 30 manufacturers for the years 1995 to 2005. The turbines from these 30 manufacturers was found to cover 85% of the market share translating to approximately 98% of the cumulative world wind power installed by the end of 2005. These were categorised into four types as are shown in Figure 4.12.

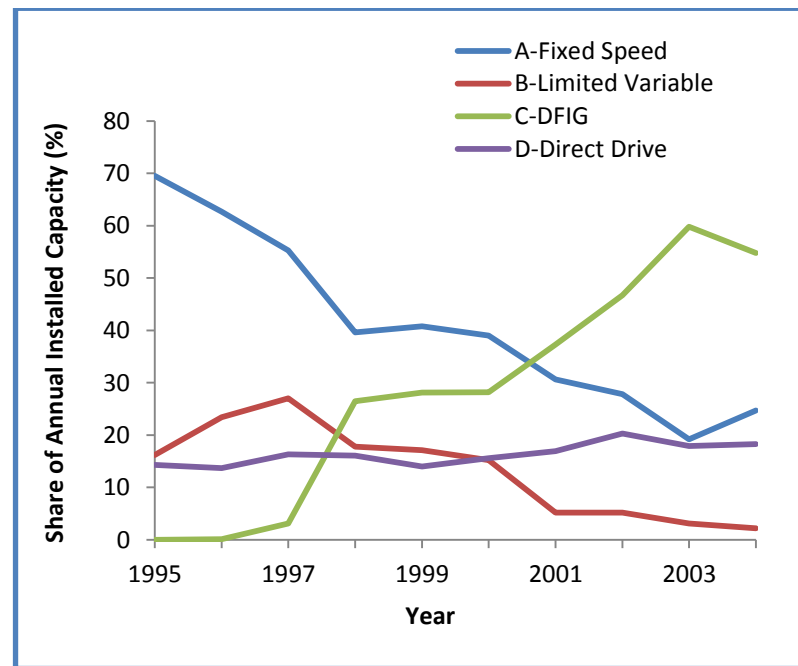


**Figure 4.12 Drivetrain Concepts Schematics.** <http://electrical-riddles.com>. Accessed April 2013

In the early 1990s, the fixed speed Type A SCIG ( Squirrel Cage Induction Generator) was the common concept and from the late 1990s very few concepts are of this type because of the advantages of the variable speed over the fixed speed especially for grid connected MW turbines. The concept has the significance of being the original concept for the early commercial wind turbines from which other

alternatives were derived. Type *B*, limited variable is no longer common though some manufacturers use the same concept for some of their turbine models such as such as Vestas' V66/1.66 MW and Suzlon's S88/ 2 MW model. However, sales of these turbine models are very low. Since the late 1990s, Type C has become the most common concept on market and was the chosen type for the reference turbine. Type *D* concept has the advantage of having no gearbox, a component with very high failure rates. However, it has a higher power loss in the power electronics compared to Type C concept, since all the generated power has to pass through the power converter.

Enercon, one of the top ten Global OEMs as discussed in Chapter 4, has been the major manufacturer of direct drive turbines since the early 1990s. Their larger turbines are wound rotor synchronous generator (WRSG) systems as opposed to the improved alternative PMSG. In the past from the early 90s to the mid 2000s Enercon global market share of wind turbines was roughly the same as the overall global market of direct drive as it monopolised this market. Figure 4.12 shows historical trends of the four drivetrain types over a period of ten years from the mid 90s to the mid 2000s.



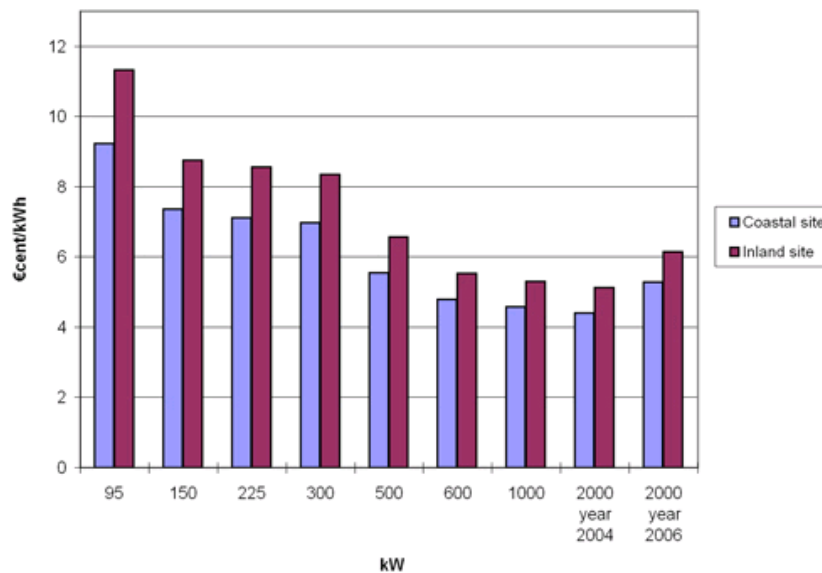
**Figure 4.13** Wind turbine drivetrain concept market penetration 1995 to 2004, Drivetrain types defined in Figure 4.12 (Hansen and Hansen, 2007)

## 4.5 Wind Energy Cost Development

The cost of energy from the wind comprises the cost of the wind turbine, the cost of installation (balance of station), annual cost of operation and project financing costs. Turbine costs are the most significant element of capital expenditure, typically around 75% of the total cost. The holistic estimation of the cost of electricity energy extracted by the wind turbine also involves assessment of the turbine performance in the form of annual energy yield (AEP).

Typically, the capital cost of a turbine is in the range of 1m €/MW (1.2m \$/MW) (Arup, 2011). The initial capital costs also include balance of station costs which are necessary for the installation of the turbine at the site, notably: transportation, foundations civil infrastructure and grid connection costs. The Operation and Maintenance (O&M) cost include fixed annual costs and variable costs dependent on the yield.

As the turbine average size has increased over the years since the 1980s, the capital cost of wind energy has declined markedly as illustrated in Figure 4.14.



**Figure 4.14 COE trends for onshore and offshore wind turbines (Morthorst, Auer et al., 2009).**

Cost reductions were coupled with dramatic increases in performance from advanced turbines and larger turbines (Schwabe, Lensink et al., 2011; Lantz, Wiser et al., 2012; Milborrow, 2012). This resulted in a reduced overall cost of energy in \$/MWh. Historical lows in wind energy capital costs were observed around 2003 worldwide. Global trends based on data mainly from America and Denmark suggested levelised cost of energy (LCOE) decreased by a factor of more than 3 times from around 150 \$/MWh in the 1980s and 1990s to about 50 \$/MWh as shown in Figure 3.3 (Lantz, Wiser et al., 2012b).

In a turn of events after the historical lows around 2003 the trend in declining capital cost came to an end and sudden increases were observed until the latter 2000s (2007-2009). As discussed in the last chapter, similar to other energy technologies, this was due to increases in energy demand and rises in material prices and labour costs among other factors. Turbine costs are sensitive to changes in material costs and price rises in steel and other materials. Capital costs also increased in that period to restore profitability of some of the turbine manufacturers on the market. The other possible reason was the increase in demand of turbines and components (Junginger,

Van Sark et al., 2010). Although upscaling brought about increased performances, it also resulted in high turbine costs contributing to further increases in capital costs for wind energy.

China was an exception to this global trend as wind energy technology was experiencing a boom in this low labour costs country and a few manufacturers in the country emerged and joined global leaders in the industry. Consequently China had lower capital costs than America and Europe.

From the late 2000s, global cost reduction trend recommenced but the costs are still higher than the historical lows (Lantz, Wiser et al., 2012). As performance improvements result due to continued research, notably in overcoming barriers such as continued upscaling and exploitation of low wind speeds, onshore wind energy technology has continued to be attractive in a number of countries. According to a 2008 report by the private consultant BTM consult, cost remained the biggest barrier to the growth of wind energy but was expected to fall by between 20% and 35% in the long term. Several studies suggest that the cost of energy from wind will continue to fall based on continued performance improvements associated with upscaling and design advances (EWEA, 2012; Lantz, Wiser et al., 2012; Milborrow, 2012; Lantz, Wiser et al., 2012b).

#### **4.5.1 Cost Development and Innovation**

The cost of wind-generated electricity can be effectively reduced by steady improvements in both wind turbine design and operation since the conversion of wind energy into electricity is a highly capital-intensive and maintenance-demanding technology (Molenaar, 2003). The major factor in the reduction of the cost of wind energy for over two decades up to 2004 was the increase in the size of individual wind turbines and wind farm projects together with engineering and design improvements as well as a direct consequence of dramatic growth in market.

Some literature concludes that wind turbine design changes over the years are not in any significant degree a path to cost reduction (Gardner, Garrad et al., 2003). For example, variable speed may offer a little more energy capture, but this is largely

offset by added cost. It should also be noted that design improvements resulting in increases in the turbine cost might have an overall positive impact on the cost of electricity production. It is argued that design changes have been driven by market demands, such as improved noise regulation, better power output quality, and more reliable gearboxes (Gardner, Garrad et al., 2003). Satisfying these market demands resulted in a reduction in the capital costs as well as electricity price reductions. It is therefore necessary to take a holistic approach when considering the impact of design or configuration changes.

One of the reasons behind the fast technological progress of wind energy has been the ability of the sector to adapt from other industries. An example is in the area of aerodynamics where the use of new materials in aircraft manufacturing and associated cost reductions has been transferred to wind turbine blade manufacture. According to Neij (2003) some innovations found for wind energy can be used in other technologies.

Turbines manufactured from the early 1980s to mid 1990s used mainly standard components with the exception of blades. With an increase in production and installation special components started being designed for turbine use only. For example, it is necessary to design and produce specialised larger ball bearings for MW turbines.

However, the major factor in the reduction of the cost of wind energy over the last 20 years has been the increase in the size of individual wind turbines and wind farm projects together with engineering and design improvements to the blades, electronic controls and weight reduction of individual components that impact their manufactured costs.

## **4.6 Discussion**

The status of wind energy globally has been shaped by energy sector challenges such as the need to sustainably ensure electricity supplies at the same time as cutting greenhouse emissions in the face of global economic turmoil. The energy demand boom in emerging economies such as China and India have seen increased growth in



the past few years and has resulted in China leading not only in growth but in the share of global cumulative installed capacity. However, almost no Chinese turbines are installed outside China because although they are cheap, they are relatively unreliable, resulting in low yields. Although the Danish company Vestas is still the leading manufacturer of MW turbines, the rise of turbine manufacturers in China and India might result in that region influencing the trend not just of wind energy technology, but the component designs provided the reliability of these turbines is improved.. It might be interesting to investigate if in the future there might be significantly high enough influence resulting in a “Chinese concept” in the same way as the “Danish concept” or has the turbine design been developed enough with no further significantly disruptive concepts anticipated.

As a technology, wind energy is a fully commercial technology, but there are still outstanding RD&D to deliver energy at full economic potential. However for wind to continue to reach parity with conventional sources and increase its competitiveness without support, innovation will continue to play a major role. The development of wind turbine technology has been more incremental as the technology evolved over the years mainly in upscaling kW turbines to the current MW turbines. This has resulted in some technical challenges and barriers which were overcome by introducing innovative alternative components at component levels such as the move from fixed speed to variable speed and the introduction of direct drive drivetrain system.

Turbines are made of different components with different functionalities whose assessment include studies in different engineering fields such as aerodynamics, electrical, electronics, structural and construction. Some components are highly specialised for wind turbines such as the aerodynamic blades whereas some such as gearboxes and bearings, find use in other sectors. The fields of influence for the different technologies have an influence on the methodological approaches to assessment. Although the turbine is a cost centre, there is need to further disaggregate the turbine into components for detailed analysis. As different components have different cost influencing factors depending on load, material or field of study, it becomes important to assess them differently. For example,

aerodynamics plays an important role in the design as well as assessment of blades whereas electrical principles will be a major influence for the generator. In addition to the disaggregation into individual components for detailed assessment, lower levels of disaggregation are also important. Isolating subsystems such as the rotor, drivetrain, nacelle and tower can assist in assessment by parametric modelling at reduced level of detail.

Cost reduction trend has been observed and forecasted in a number of studies. At the same time, the turbine design has evolved incrementally in size with some radical changes at component level such as the removal of the gearbox in direct drive systems. It is therefore important to analyse cost trends for the technology or the wind turbine in the context of major conceptual changes to the turbine and its components. Without such improvements to analysis methods, any cost assessment will be based on the assumption of a standard turbine that has not gone through innovation and will not reflect the technical developments that have taken place over the years. The development of methods of assessments that take change into account are crucial for emerging energy technologies whose competitiveness is dependent on innovation.

## **4.7 Conclusion**

Wind energy technology is an established low carbon energy supply technology commercial technology. In terms of technology maturity, onshore wind energy is a leader in the mechanical renewable energy technology category with other technologies such as marine and offshore wind, and overall it is at a more advanced deployment stage than most other renewable technologies. Global cumulative installed capacity of wind energy has increased steadily over the years with remarkable growth rates notably more recently in emerging countries like China and India. Awareness of climate change and greenhouse gases consequences has resulted in more countries supporting renewable energy technologies initiatives and policy such as wind energy and has resulted in increases in demand of wind turbines.

The wind turbine constitutes the largest cost centre wind energy cost assessment. Inherently, cost assessment of wind energy technologies begins with the detailed

analysis of a reference turbine from which further analyses can be derived. This turbine will be based on the typical turbine model on the market, the 3 bladed horizontal axis turbine with a 3 stage gearbox and a double fed induction generator (DFIG) with a partial power converter. This detailed engineering assessment is discussed in the next chapter.

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## 5 Engineering Assessment of Weight

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### 5.1 Introduction

In this chapter, the weight of the model turbine is estimated by engineering assessments. Wind turbine technology has evolved over the years from the standard early commercial turbine designs as was noted in the last chapter and still has the potential to change. Analysing the impact of innovation on the technology requires an initial assessment of a reference turbine to benchmark any subsequent changes. The detailed engineering assessment necessary for obtaining the cost of a typical representative commercial MW reference turbine is addressed in this chapter. The cost of the majority of the turbine components is related to their weight. This chapter will focus on the development of upgradeable models for weight estimation of the reference turbine components. The results will be used for the cost estimations of the components and the turbine in the following chapter.

One of the common 2 MW turbines on the market, the Vestas V80, was chosen to define the “2 MW reference turbine” for the analysis which is based on the commonly used “Sunderland” costing model outlined by Harrison (2000), the main source for the engineering assessments for this study. The model involves deriving component physical attributes in terms of weight and translating the weight to cost. The specifications of the V80 model from the manufacturer, Vestas, together with relevant information from other turbine manufacturers and studies are used to estimate the weight of individual components of the 2 MW reference turbine. The detailed assessment involves disaggregating the turbine into individual subsystem and components to capture major cost centres and developing models to estimate weight for each of these. Engineering weight and cost assessment of the Vestas 2 MW turbine is done to the greatest possible levels of detail that will allow the capturing of technical cost drivers for the available data and resources.

The next section of this chapter, section 5.2 gives an introduction to detailed assessment of the turbine. Section 5.3 outlines important parameters used for the assessment, and also provides a background of the 2 MW Reference Turbine providing a justification of the choice. Section 5.4 outlines the proposed approach to modelling component weights and gives component weight results for the reference turbine. Unless stated, the equations used in this section are based on the Sunderland model as given in Harrison (2000). Section 5.5 is a discussion of chapter and the results and section 5.6 concludes the chapter leading to the cost assessments in the following chapter.

## **5.2 Wind Turbine Detailed Assessment**

As mentioned earlier, cost of the wind turbine is a significant cost centre for wind energy technology, typically 70% to 75% of the total installed capital costs and about 65% of the total wind energy costs (Hau, 2006; Jamieson, 2011). The assessment of the cost of energy from wind is therefore, highly dependent on the turbine physical attributes. When comparing conventional energy power plants, rated power is the significant parameter for indicating performance as well as for economic comparisons. However, for renewable energy converters the source of energy is of low density and of intermittent nature and converters do not operate at full rated power most of the time. The physical size of the energy converter and the output are dominant parameters in determining the cost of energy generation from a renewable technology such as wind energy. The weight of the wind turbine components therefore plays an important role in determining the cost of energy generation from wind. However, for some electrical and control components, the rated power is the main driver to cost.

The turbine physical attributes are dependent on the turbine designs driven mainly by cost reduction, environmental impact and weight, while at the same time, conforming to international standards and adhering to regional and national policy regulations. Turbines are designed to withstand all the loads they are subjected to under varying operational conditions. The estimation of cost based on the turbine design is guided

by these factors that ensure a well balanced wind turbine that serves the function of generating electricity.

Wind turbines are assembled from a mixture of commercially available items and specially designed and fabricated items. Commercially available items typically have lower costs when bought in volume for mass production and this brings costs down. Specialised items are expensive at prototype level. Wind turbine components also exhibit differences in the way they are manufactured and assembled as well as in the major materials used thus requiring cost assessment at component level.

Detailed engineering assessments require high levels of disaggregation but this comes with increased complexity. Complex models for assessing weight and cost of numerous components require time and effort to construct and might give distorted results due to high levels of possible errors in the modelling processes. In as much as detailed assessment is required, there is a need to make reasonable assumptions to reduce system complexity without losing the benefit of improved data methods from a detailed analysis. A clear definition of the turbine system and levels of aggregation becomes important in an attempt to develop detailed models for the assessment of the wind turbine system.

Components are sold to the manufacturers by external suppliers or provided from within the company as an assembly of subcomponents. One way of defining the turbine system is to divide it into components as they are supplied. A gearbox as an example, although made up of hundreds other mechanical subcomponents going down to screws, bolts and nuts, is sold as one unit. Even though these subcomponents can be cost modelled as individuals, disaggregating the turbine system down to these subcomponents would require vast amount of resources and effort to come up with accurate and relevant data. It would also limit the further use of such data for other less aggregated methods of assessment such as parametric modelling as intended in this study.

Another approach is to divide the turbine into three or four manageable subsystems. This is done having a foresight of how the models might be later upgraded to explore technological changes. The turbine can be divided into the subsystems as discussed

in Chapter 4: the rotor (aerodynamic components), the drivetrain (electrical and mechanical), the nacelle (structural) and the tower (support structure). The drivetrain and the nacelle can be simplified into one to reduce the number of subsystems to three as shown in Table 5.1. This method of aggregation improves modelling simplicity and resources can be optimised focussing more on the subsystem which is affected mostly by any configuration changes.

| Level I-Aggregated                 | Level II- Medium               | Level III -Detailed  |
|------------------------------------|--------------------------------|--|
| <b>1. Rotor</b>                    | Blades , Hub., Pitch mechanism | Blades + Root attachment   |
|                                    |                                | Pitch Mechanism  |
|                                    |                                | Hub  |
| <b>Nacelle + Nacelle Equipment</b> | Nacelle                        | Bedplate   |
|                                    |                                | Nacelle Covering   |
|                                    |                                | Yaw Mechanism  |
|                                    | Drivetrain (Nacelle Equipment) | Shafts   |
|                                    |                                | Bearings   |
|                                    |                                | Gearbox  |
|                                    |                                | Generator  |
|                                    |                                | Mechanical Equipment (Brakes, High speed shaft A/C, Lubrication) |
|                                    |                                | Electrical Equipment (Cables/Power Electronics/Control)          |
| <b>Tower</b>                       | Tower                          | Tower  |

**Table 5.1 Wind Turbine Disaggregation Levels**

In defining the turbine system, the study therefore endeavours to include all significant cost drivers. Grouping components into a subsystem is based on the assumption that the components in the subsystem behave in similar ways or the components have some common characteristics. The 2 MW reference turbine detailed costing will be based on Level III disaggregation level given in Table 5.1 (Fingersh, 2006; Hau, 2006; Maples, Hand et al., 2010). Other subsequent assessment methods will be partly based on lower levels of disaggregation (Level II and Level I). Modelling small components such as screws and springs which might behave in isolation from the main component is beyond the scope of this work. Reasonable assumptions are however made to define the system consistent with previous studies (Fuglsang, Bak et al., 2002; Bywaters, John et al., 2005; Polinder, Van Der Pijl et al., 2006; Maples, Hand et al., 2010).

### 5.3 Reference Turbine Specifications

Detailed generic assessment methods entail careful consideration in the choice of the input parameters for the standard or reference turbine and its system definition. A number of parameter values need to be chosen from different sources such as existing databases and published reports or studies, but where these are limited, parameters can be estimated. Technical specifications of the Vestas V80 available from the turbine model's catalogues and Vestas and other relevant manufacturers' website were used to derive possible operational and geometrical values for use in the weight and cost assessment of the 2 MW reference turbine. Wind energy authoritative and industry representative energy organisations such as the International Energy Agency (IEA), the European Wind Energy Association (EWEA), RenewableUK (formerly British Wind Energy Association (BWEA)) in the UK are examples of relatively reliable sources of data. A database of large commercial MW turbines on the market online previously on the German Wind Energy Association (BWE) website (BWE, 2010), but now on a separate website (WEM, 2012), was used for comparing and validating chosen parameters and weight models results.

#### 5.3.1 Operational and Geometric Parameters

This section will define turbine system operational and geometric parameters necessary for the detailed assessment models to be developed. Operational parameters of the wind turbine generator are related to energy production. These are linked to the rated wind speed  $V_r$  and rotor tip speed. They depend on the design speed regime (fixed or variable speed operation) and the method of power control (pitch, stall or active stall).

The major geometric parameter that characterises the size of the turbine is diameter ( $D$ ) of the rotor of blades. The turbine size can also be denoted by the radius ( $R$ ) or swept area ( $A$ ). This geometrical parameter plays an important role in the estimation of turbine weight and cost. However, turbine costs are not just determined by the rotor diameter. The tower height ( $H$ ) and the installed generator power ( $P$ ) have an impact on the physical attributes, hence the cost and the turbine performance. The



geometric and operational parameters are discussed below before a summary of the values for the 2 MW reference turbine.

### **Rated Power ( $P$ )**

The rated power or the nameplate capacity determines the amount of energy captured by the turbine. Rated power is dependent on the machine configuration but the energy produced (yield) is dependent on other site related and operational factors such as losses, availability and wind speed. The rated power is given in equation 5.1.

$$P = \frac{1}{2} \rho A V_R^3 C_p \eta \quad 5.1$$

Where  $A$  is the rotor swept area in  $\text{m}^2$  proportional to the square of the rotor diameter ( $D$ );  $V_r$  is the wind speed in  $\text{m/s}$ ;  $\rho$  is the air density in  $\text{kg/m}^3$ ;  $C_p$  is the aerodynamic power coefficient with a theoretical maximum called the Betz limit = 0.59; and  $\eta$  is the drivetrain efficiency for all the equipment such as the generator and the gearbox.

The 2 MW rating was chosen to reflect current MW trends on the market and allows scaling up to larger turbines such as the 7.5 MW turbine on the market and the 10 MW turbine being researched (Polinder, Bang et al., 2007; Hendriks, 2008; Maples, Hand et al., 2010; UPWIND, 2012).

### **Diameter ( $D$ )**

The diameter of a wind turbine ( $D$ ), is the independent parameter on which other parameters depend on (Hau, 2006). For a given power level, the derivation of the rotor diameter is generally the start of the aerodynamic design of the rotor. The larger the diameter of its blades, the more power it is capable of extracting from the wind. The Vestas V80 turbine has a diameter of 80 m and this value will be used for the 2 MW reference turbine diameter. Some manufacturers design alternative models for the same power rating with higher diameters to capture more energy. The Vestas V90 model has the same rating of 2 MW as the V80 but the diameter is 90 m and captures more energy than the V80. It is usually more beneficial to increase the power rating  $P$  with increase in  $D$ .

### Turbine Hub Height ( $H$ )

The turbine hub height as shown in Figure 5.1 or tower height is an important parameter in the design of wind turbine components. It has an influence on other parameters such as the energy yield, tower fatigue loads, tower mass and tower's natural frequency (Harrison, Hau et al., 2000).



**Figure 5.1** Turbine Hub Height-Source <http://www.powernaturally.org>

Winds at higher heights have more power, but this means higher towers with increased costs. There is a trade off between benefits of extra energy from higher wind speeds and the cost of turbines. At higher heights there are higher wind speeds because of reduced drag compared to that at the surface. The variation in wind velocity with altitude, called wind shear, is most pronounced near the surface. The change in velocity for different heights  $H_1$  and  $H_2$  can be estimated using the following power law (Wharton and Lundquist, 2012):

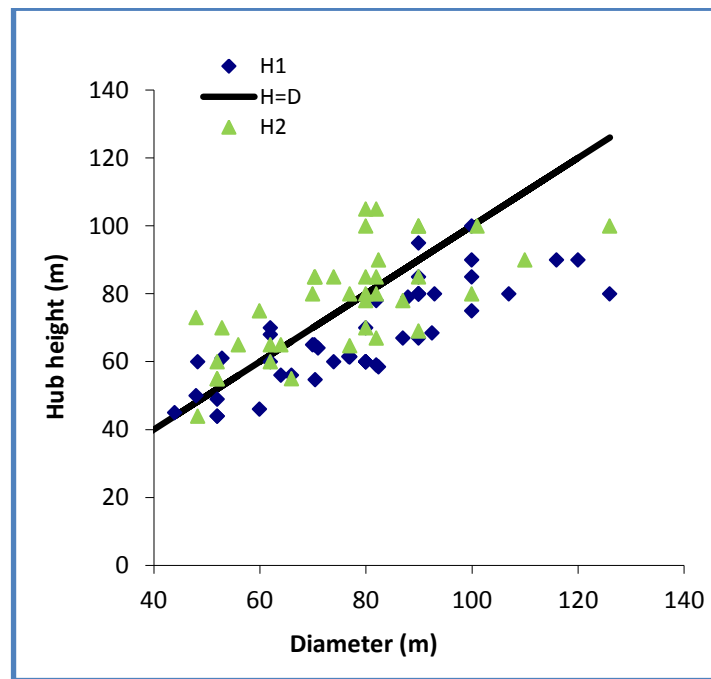
$$V_2 = V_1 \left( \frac{H_2}{H_1} \right)^\alpha \quad 5.2$$

Where  $V_1$  and  $V_2$  are the wind speeds at the two heights and  $\alpha$  is the wind shear.

Typically, in daytime  $\alpha$  is approximately equal to  $\frac{1}{7}$ , implying that the wind speed rises proportionally to the seventh root of altitude. Doubling the turbine height of a turbine increases the expected wind speeds by 10% and the expected power by 34%. This however implies increased tower weight and hence cost.

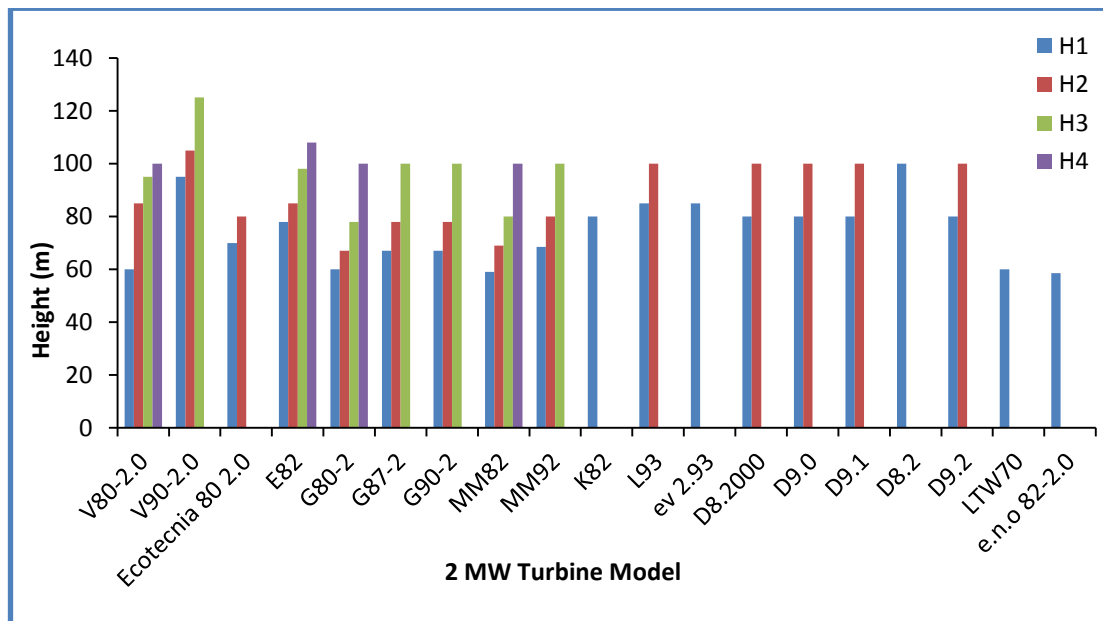
The choice of the hub height is based on the site of installation with areas with lower wind speeds getting turbines with relatively higher heights. It used to be assumed that the hub height was nearly equal and or fixed with the diameter (Burton, Sharpe et al., 2002; Hau, 2006). However, the trend for large scale MW turbines has seen design of turbines with average hub heights of sizes less than the diameter (Gardner, Garrad et al., 2009).

Generally, for large MW turbines, the average height is usually less than or equal to the diameter as seen in Figure 5.2 which plots two sets of hub height data,  $H_1$  and  $H_2$ , where for a given turbine model  $H_2 > H_1$ . As the diameter increases, moving to the right, most heights lie below the  $H=D$  line.



**Figure 5.2** Height vs. Rotor Diameter for MW turbines. Data sources from (WEM, 2012)

Commercial turbines are available from manufacturers typically with three or more tower height options with higher heights more suitable for low wind speed sites. These are defined in this thesis as  $H_1$ ,  $H_2$ ,  $H_3$  and  $H_4$  with ascending heights from  $H_1$  to  $H_4$ . The Vestas V80 turbine is designed for a range of four heights depending on the customer needs. A typical range is:  $H_1 = 60$  m,  $H_2 = 85$  m,  $H_3 = 90$  m and  $H_4 = 100$  m. The average height of 85 m is used for the 2 MW reference turbine and for high wind speed areas and a value of  $H = 60$  m, is also used for comparison purposes. Figure 5.3 is plot of commercial turbines from a database which shows the general trend of hub height ranges for the major 2 MW turbines on the market. The averages for  $H_1$ ,  $H_2$ ,  $H_3$  and  $H_4$  given in Figure 5.3 are 74 m, 88 m, 97 m and 102 m respectively.



**Figure 5.3 Commercial 2 MW turbines hub heights (BWE, 2010; WEM, 2012)**

The Vestas V90 (the 2 MW model), similar to the V80 but with a diameter of 90 m has a higher range of heights: 80 m, 95 m, 105 m and 125 m to accommodate longer blades.

### Tip speed ratio ( $\lambda$ )

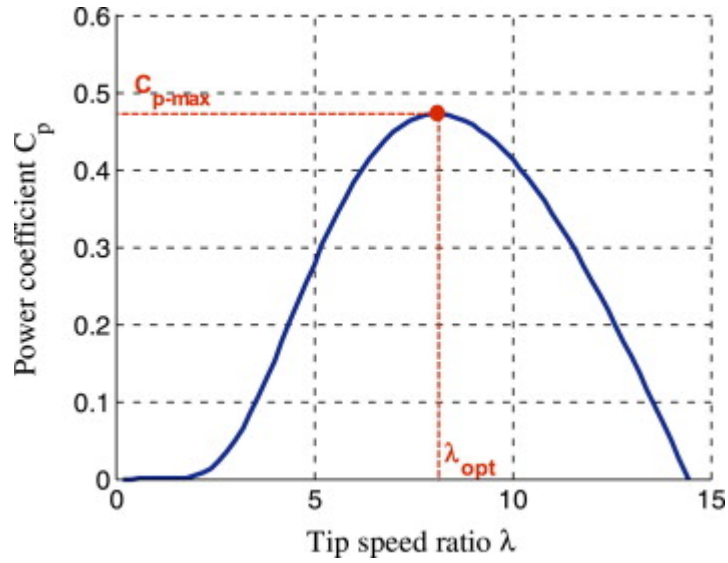
The tip speed of the turbine rotor is the product of the turbine rotational speed and radius of turbine. The tip speed ratio (TSR) or  $\lambda$  is the ratio between the tip speed and the actual wind velocity.

$$\lambda = \frac{\omega R}{V} \quad 5.3$$

Where  $V$  is the wind speed and  $\omega$  turbine rotational speed and  $R$  the rotor radius ( $\omega R = V_t$ , the turbine tip speed). Many parameters for estimating turbine performance show a strong dependence on the tip speed ratio of the rotor. A high TSR has the advantage of reducing mass in the rotor and the drivetrain, but there is an increase in dynamic loading, which will also have an impact on the drivetrain system.

For onshore turbine, a high speed rotor is not attractive due to noise at high tip speeds, and so TSRs tend to be lower than offshore. Offshore turbines can have high

TSR as noise has no impact on the social environment (Sahin, 2004). Figure 5.4 below shows the relationship between tip speed ratio and the turbine aerodynamic performance measured by  $C_p$ .



**Figure 5.4** Typical  $C_p$  vs.  $\lambda$  curve (Masmoudi, Abdelkafi et al., 2011)

The tip speed ratio  $\lambda$  for a 3 bladed turbine is normally between 5 and 8. From the Vestas V80 datasheet (Vestas, 2012) the rotational speed is 16.7rpm at a rated wind speed of 15.6 m/s, giving a tip speed ratio of 5. For optimum aerodynamic performance, at the maximum coefficient of power  $C_p$  the design tip speed  $\lambda_d$  is chosen to be 7 for the 2 MW reference turbine.

### Design wind speed ( $V_d$ )

The design wind speed ( $V_d$ ) is defined as the maximum wind speed at which the maximum coefficient of performance ( $C_p$ ) is achieved with  $\lambda = \lambda_d$  (or  $\lambda_{opt}$  as in Figure 5.4). The design wind speed can be estimated from the turbine tip speed  $V_t$  from the relationship:

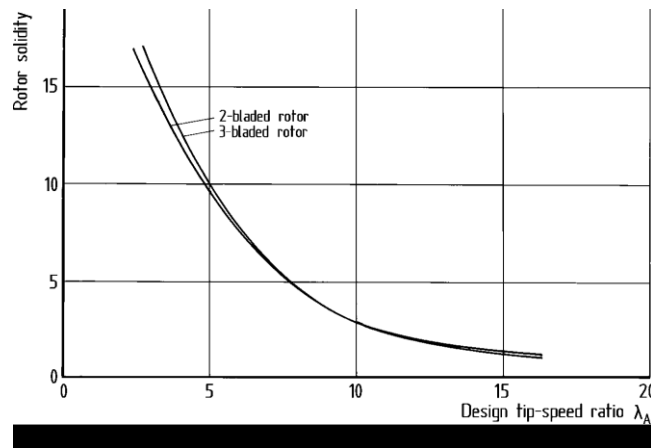
$$V_d = \frac{V_t}{\lambda_d} \quad 5.4$$

$V_d$  is important for calculating the weight of the load bearing element of the turbine blades. Although variable speed turbines run over a wide range of speeds, for the

V80 the turbine tip velocity speed,  $V_t$ , is calculated from the turbine nominal speed, 16.7 rpm, and diameter,  $D = 80$  m, giving a value of 70 m/s at  $\lambda_d = 7$  when  $C_p$  is a maximum value. Substituting these values into equation 5.3 gives  $V_d = 10$  m/s for the 2 MW reference turbine.

### Solidity (S)

Solidity is the ratio of total blade area facing the airstream to the full rotor disk area expressed as a percentage. Figure 5.5 shows the relationship between the rotor solidity and the tip speed ratio.



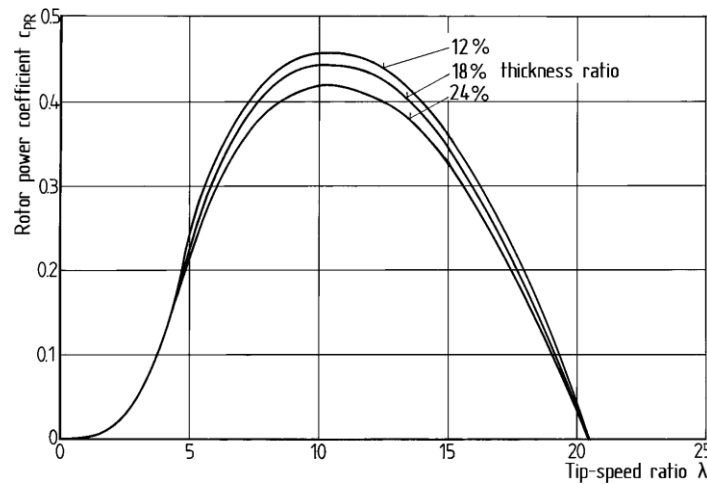
**Figure 5.5 Rotor solidity as a function of the tip-speed ratio (Hau, 2006)**

Solidity increases are associated with increasing tip speed, with a resulting increase in noise as mentioned above. This condition results in loading issues and places a great demand on design leading to complex concepts requiring high specific strength material and carbon reinforcement. Typically, for  $\lambda = 5$ ,  $S = 10\%$  and for  $\lambda = 7$ ,  $S = 6.5\%$ . In this thesis a solidity of  $S = 6.5\%$  for a design tip speed of 7 is used.

### Blade thickness (t)

The blade thickness is important in defining the turbine blade profile. The blade thickness changes along the blade, but the ratio between the chord and the thickness remains constant and this ratio is used when defining the blade's thickness. The blade thickness ratio is normally referred to as simply "blade thickness" (t). Choice of blade thickness is a balance between aerodynamic efficiency, rotor blade stiffness and strength requirements. Thin blades have high aerodynamic efficiency as shown

in Figure 5.6 and in contrast structural requirements demand a thick cross section for load bearing elements (Hau, 2006).



**Figure 5.6** Influence of rotor blade thickness-to-chord ratio on the rotor power coefficient (Hau, 2006)

The National Advisory Committee for Aeronautics (NACA) defines blade profiles for aerospace purposes as well as for wind turbine blades using 4 or 5 digit codes. The last two digits of the code indicate the blade thickness which for wind turbines is usually in the range 15-20%. For example, NACA 23018 blade has a maximum thickness of 18%. The Vestas V80 blade profile is composed of a NACA 63 XXX blade profile between the blade tip and its centre, and an FFA W3 XXX blade profile between the centre of the blade and the hub (Clement, Guy et al., 2008). Vestas does not specify the last 3 digits for commercial reasons. It is assumed the last two digits is 15, so a value of  $t=15\%$  will be used for modelling purposes. The maximum chord for the Vestas V80 turbine blade is 3.5 m, and therefore the thickness at the root is assumed to be around 0.525m. Figure 5.7 shows a similar profile NACA 63 415 with a blade thickness ratio  $t$  of 15%.





**Figure 5.7** Turbine Blade Profile (Clement, Guy et al., 2008)

### Material Properties

The main materials used in wind turbines are polymer composites for the blades and nacelle, steel for structural elements and other material like copper for the electrical components. Table 5.1 show the typical share of material use for a wind turbine in terms of weight.

| Material | Concrete | Steel | Copper | Aluminium | Glass fibre | Adhesives | Other Materials |
|----------|----------|-------|--------|-----------|-------------|-----------|-----------------|
| Share %  | 1.3      | 89.1  | 1.6    | 0.8       | 5.8         | 1.1       | 0.4             |

**Table 5.2** Wind Turbine Raw Materials (Rogowsky and Laney-Cummings, 2009)

The main material for the wind turbine is steel which is used in the tower, the hub, and structural components. Drivetrain equipment is also partly made of steel. Table 5.3 below gives the important properties for steel and other major materials.

| Material        | Admissible Strength<br>( $\sigma_{adm}$ ) MPa | $\rho_m$<br>kg/m <sup>3</sup> | $\rho_m/\sigma_{adm}$<br>$\times 10^{-6}$ |
|-----------------|---|-------------------------------|---|
| Steel           | 110   | 7800                          | 71.0                                      |
| Glass-polyester | 45  | 1800                          | 40.0                                      |
| Glass-epoxy     | 56  | 2000                          | 33.3                                      |
| Carbon-epoxy    | 200   | 1500                          | 7.5                                       |
| Wood- epoxy     | 12  | 50                            | 45.8                                      |

**Table 5.3** Main Materials' Properties (Harrison, Hau et al., 2000)

### 5.3.2 The 2 MW Reference Turbine

A reference turbine with a rated power capacity ( $P$ ) of 2 MW was chosen for the detailed assessment. The majority of commercial large turbines on the current market are MW turbines. The ideal reference turbine would be in the lower power rating range of the MW turbines which can then allow upscaling to larger turbines of about 10 MW or better still 20 MW as considered in literature (UPWIND, 2012). Very few models of 1 MW power rating exists and the 1.5 MW are also relatively fewer compared to the 2 MW rating, the most common in the lower range of the MW turbines. Significant data on turbine properties and performance is available for use for V80 turbine model (Vestas, 2012; WEM, 2012).

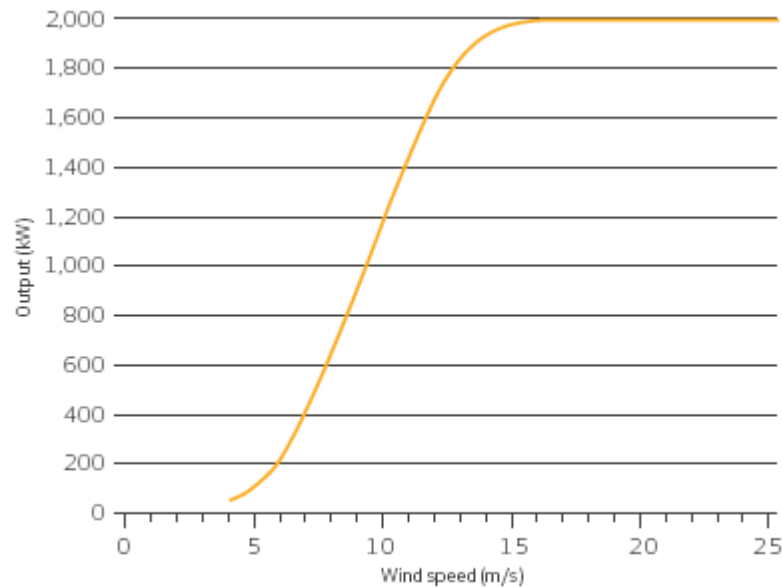
The chosen Vestas V80 2 MW model is a very common model in operational wind farms in the UK as shown in Table 5.3. With the industry's largest global market share and most advanced technologies, Vestas is the world's leading supplier of wind energy solutions (Vestas, 2011; Vestas, 2011b). Built on a tried and tested design platform, by mid 2012, Vestas had installed more than 4,000 V80 turbines around the world, with at least eight new V80s installed worldwide every week. This makes the V80-2.0 MW one of the most thoroughly tested turbines on the market (Vestas, 2012). As of 2012 the UK had a total of 176 V80 turbines nearly 5% of the market share of all turbines in operational windfarms (BWEA, 2012).

The V80 is designed around standard components which can be supplied by many suppliers. This makes it a good choice for a reference turbine for analysis models that will be used to assess different turbines. It is also designed to optimise performance and output at any high wind class site and has good productivity record. Vestas designs concepts with cost reduction as one of their aims and the V80 is built for reliability and reduced maintenance with innovative lubrication key components such as blade bearings and yaw systems. The components are well placed in a way to reduce service time and manpower and most rotating parts are shielded and maintenance can be carried out with standard tools. Another advantage of the V80 is that it is designed to be site independent (Vestas, 2012). All these factors favour the choice of the V80 as the basis for the 2 MW reference turbine for the development of

detailed models for engineering assessment for this work. Table 5.4 lists the major technical specifications as given by the manufacturer which will be used to estimate other operational parameters for the 2 MW reference turbine and the power curve for the Vestas V80 turbine model is shown in Figure 5.8.

| Parameter                                  | Value  |
|--|--|
| Diameter, m                                | 80   |
| Area, m <sup>2</sup>                       | 5027   |
| Height, m                                  | 60, 85, 90, 100                              |
| <b>Operational Parameters</b>              |  |
| Rated wind speed, $V_r$ , ms <sup>-1</sup> | 15.6   |
| Cut-in /Cut-out, ms <sup>-1</sup>          | 4/25   |
| Nominal rotational speed $V_r$ , rpm       | 16.7   |
| Operational range of $V_r$ , rpm           | 9-19.1                                       |
| $C_p$ at rated power                       | 0.2  |
| <b>Component Details</b>                   |  |
| Gearbox                                    | Three-stage planetary/helical , 1:100.5      |
| Generator                                  | 4-pole doubly fed induction generator (DFIG) |
| Power Regulation                           | Pitch regulated with variable speed          |
| <b>Tower</b>                               | Conical tubular steel                        |

**Table 5.4 Vestas V80 Technical Specifications (Vestas, 2012)**



**Figure 5.8 Vestas V80 power curve from the manufacturer.**

## 5.4 Turbine Weight Assessment

The model that was used for this work is based on the so called “Sunderland model referred to in a number of studies on engineering assessment of wind turbines

(Harrison, Hau et al., 2000; Manwell, McGowan et al., 2002; Fingersh, 2006; Maples, Hand et al., 2010; Rivkin, Toomey et al., 2012). The Sunderland model, introduced in Section 3.3.1, was found to be the most relevant and ideal in achieving the set objectives of the detailed assessment and in analysing configuration changes especially upscaling. The US DOE NREL used it as a scaling cost model in 2005 and in further work in 2010 (Fingersh, 2006; Maples, Hand et al., 2010) and these NREL models will be used for this study where the use of the original Sunderland model has limitations and for validation purposes.

The Sunderland model mimics the machine design process and is mainly based on the determination of loading conditions which are used to develop a weight model which aims to address design issues over a range of sizes and configurations. Component weights are due to design drivers (quasi- static nominal loads) and service factors (fluctuating loads). Operational loads are analysed in detail so that load bearing sections of component, section module can be set to values that ensure stress levels are below safe levels. The main loads modelled are aerodynamic loads, forces from energy extraction such as torque and mass inertia related forces (Harrison, Hau et al., 2000).

The model uses first principles to develop estimates of the most important influences on cost design drivers. These are variables such as blade loading, torque and thrust. The model estimates loading and then determines appropriate dimensions of components for such loading. For complex components look up tables are used which relate size to loading. Using calculated sizes or dimensions, the weights of the component (assuming known densities) are calculated.

The turbine was divided into 13 subsystems or components illustrate in Table 5.1 and the derivation of the model equations for each component followed the stages:

1. Determination of design drivers affecting weight by calculating nominal loading of each component.
2. Combine load with material properties such as allowable stress and section module to define dimensions of components.

3. Develop models in the form of component weight equations and use reference model parameters to estimate the weights.
4. Use specific costs to calculate component costs from the estimated weights.

#### 5.4.1 Components Weight Equations

The equations are developed based on nominal loading conditions and or other “design drivers”. These need to be calibrated to represent actual components using two types of factors: matching factors ( $F_{matching}$ ) and service factors ( $F_{service}$ ). The general equation for the component weights takes the form:

$$W_{component} = F_{matching} \times F_{service} \times f(\text{design drivers}) \quad 5.5$$

Matching factors match the actual component weights where real component data exists. Service factors are used to account for the effects of different loading conditions due to different design options such as different control strategies. The matching factors used here for the 2 MW reference turbine were selected during the development of the Sunderland model (Harrison, Hau et al., 2000) and where necessary are corrected to reflect the current commercial turbines or those in previous studies such as the NREL studies (Fingersh, 2006; Maples, Hand et al., 2010). The service factors are chosen for each component or subsystem depending on the design options and their impact on the loading on the component.

The Sunderland model as used for the reference turbine is illustrated in Figure 5.9.

## Sunderland Based Assessment Model

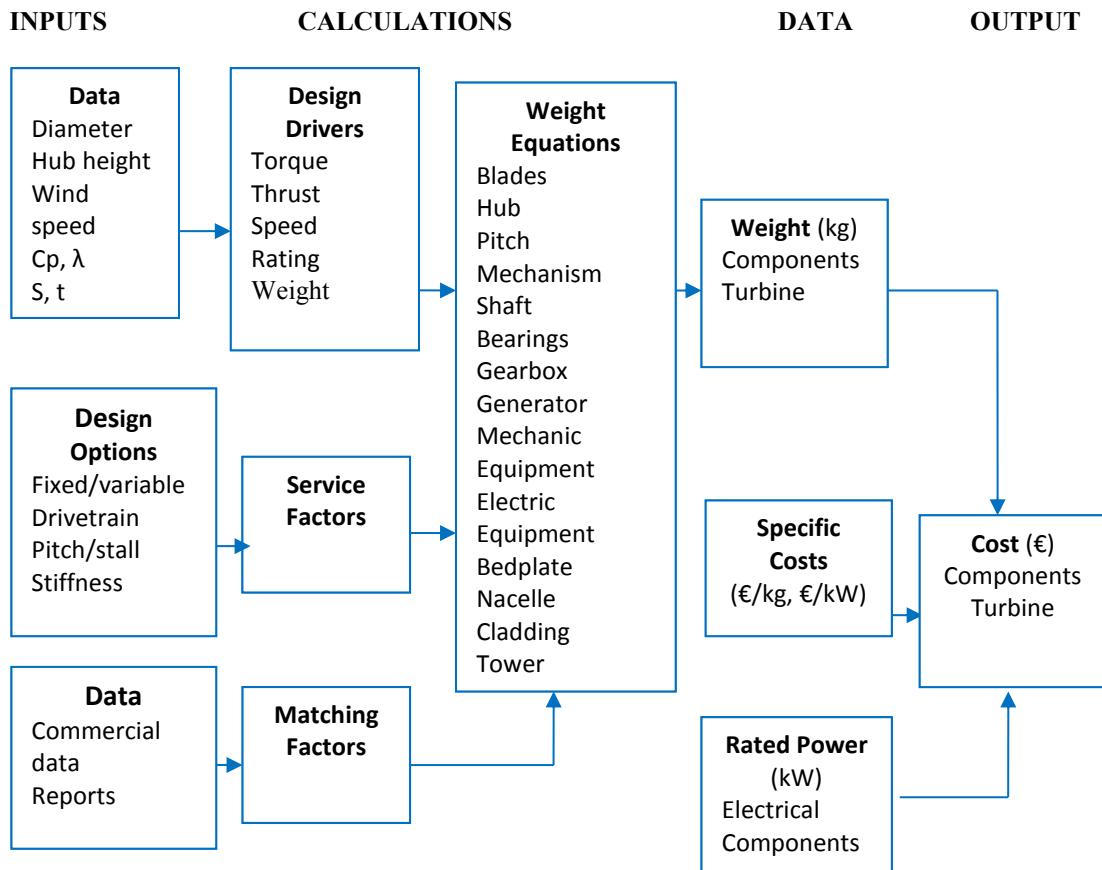


Figure 5.9 Wind turbine weight and cost modelling process for the 2 MW reference turbine based on the Sunderland Model (Harrison, Hau et al., 2000)

### 5.4.2 Components Weight Design Drivers

The main weight design drivers for the turbine components are:

- i. **Rated Torque**
- ii. **Rated Thrust**
- iii. **Rated Speed**
- iv. **Rated Power**
- v. **Weight on rotor blades**
- vi. **Other design drivers include:**
  - **Aerodynamic forces** or bending forces which the blade and hub sustain during normal conditions are used to calculate stress.

- **Fatigue** is difficult to incorporate in a cost model because there are different levels of fatigue depending on different loading conditions but assumptions can be made when choosing service factors to incorporate fatigue.
- **Stiffness** is another important design driver that has an impact on loading and consequently on cost. It is assumed that the natural frequencies of components and systems have been avoided during the design process. This is however important when modelling the tower.
- **Self weight**-As the size increases relative importance of machine weight in comparison with aerodynamic loading increases. Designs dominated with self weight have high potential for weight reduction. Assumptions have to be made for lightweight concepts. For baseline designs with diameters over 100m, self weight is important. At 80 m self weight is significant.

The major design drivers are discussed below.

### Estimation of the Rated Torque

Torque is one of the most important design drivers in the weight model and depends on wind speed, rotor diameter and rotor tip speed. Models for calculating the towerhead weights are very sensitive to rotor torque. The torque determines the size of rotary elements and other equipment such as gearbox and generator. Design alternatives for some configurations such as changes from fixed to variable speed has an impact on rated torque (Harrison, Hau et al., 2000). The rated torque is a function of the rated power ( $P = Q\omega$ ) and is inversely proportional to the rotor speed. It is calculated from:

$$Q_r = \frac{1}{16} \rho_a C_p \pi \frac{V_r^3}{V_t} D^3 \quad 5.6$$

Where from Table 5.4 for the 2 MW turbine,  $D = 80$  m,  $V_r$ , rated wind speed = 15.6 m/s,  $V_t$ , rotor tip speed = 70 m/s,  $\rho_a$ , density of air = 1.225 kg/m<sup>3</sup> and  $C_p$  is the coefficient of performance of the rotor at rated wind speed for the reference turbine = 0.2

$C_p$  must be maintained to its maximum value to optimise the output mechanical power of the turbine over the whole turbine range (Aguglia, Viarouge et al., 2009). From the V80 power curve at a rated speed of 15 the  $C_p$  is nearly 0.2. Using the power curve, Figure 5.8 and equation 5.1, accounting for the losses and ensure the power converted by the generator is 2 MW, a coefficient of performance of 0.25 is obtained. A maximum power coefficient of around 0.44 can be achieved at wind speeds around the design wind speed  $V_d$  of 10 m/s. The rated torque  $T_r$  is estimated at 1143 kNm for the 2 MW reference turbine.

### Estimation of the Extreme Thrust on the rotor

The rotor extreme thrust  $T_{ex}$  has an influence on the structural design of the tower and the structural elements. It has an effect on the weight of bearings, nacelle bedplate, tower and foundations. For the Sunderland model this is estimated as:

$$T_{ex} = \frac{1}{8} \rho_a (0.85 V_{ex})^2 C_D S \pi D^2 \quad 5.7$$

Where  $V_{ex}$  is the extreme wind speed (m/s),  $C_D$  is the aerodynamic drag factor on blades and  $S$  is the solidity. This is based on a parked rotor at wind speeds in the excess of the cut out speed when the turbine is shut down. The 0.85 factor in the extreme thrust equation is used to ameliorate the thrust to reflect that the rotor is unlikely to fail in extreme conditions (Harrison, Hau et al., 2000).

The drag coefficient  $C_D$  is important for calculation of extreme thrust. A study, (Sorensen and Michelsen, 2004), found drag for a modern parked turbine under extreme conditions to be between 1.16 and 1.32. For blades subject to cross wind the values range from 1.3 to 1.8 (Hau, 2006). To estimate the value we consider the relationship between  $C_p$  and  $C_D$  given by:

$$C_{pmax} = \frac{4}{27} C_D \quad 5.8$$

Where the maximum power coefficient,  $C_{pmax}$  is 0.44 for lift, and 0.2 for drag. For parked blade we use  $C_{pmax} = 0.2$ , which from equation 5.8 gives  $C_D = 1.35$ .



## Extreme wind speeds

Turbines are designed to withstand a certain level of loading caused by extreme wind events. Madsen estimated extreme wind speed that a parked rotor may experience that causes ultimate loading as 45 m/s (Madsen, 1999). Commercial turbine manufacturers define their design extreme wind and for large MW turbines such as the REpower 6M it is 70 m/s. Table 5.5 shows survival wind speed of some commercial 2 MW commercial turbines (WEM, 2012).

| Manufacturer     | Model            | Survival Wind speed $\text{ms}^{-1}$ |
|------------------|------------------|--------------------------------------|
| Alstom Ecotecnia | Ecotecnia 80 2.0 | 60                                   |
| Gamesa           | G80-2            | 55.8                                 |
| REpower          | MM82             | 49                                   |
| Lanco Wind       | L93              | 59.5                                 |
| De Wind Europe   | D8.2             | 57.4                                 |
| Average          |                  | 56.5                                 |

**Table 5.5 Survival wind speeds for commercial 2 MW turbines**

According to the Beaufort scale, which defines 12 wind speed categories ranging from “calm” at  $0 \text{ ms}^{-1}$  to extreme winds over  $32.7 \text{ ms}^{-1}$ , wind speeds in the range 28.5 to 32.6 m/s occur in a violent storm and speeds greater than 32.7 m/s occur in a hurricane. An extreme wind speed of 55 m/s is used with a drag coefficient  $C_D$  of 1.35 for parked blades and the solidity of 6.5% to give an extreme thrust of magnitude 590 kN.

Table 5.6 is a summary of the values of the main geometric and operational parameters for the 2 MW reference turbine as well as the major design drivers estimated based on the Vestas V80 turbine specifications given in Table 5.4. The other component specific parameters and service factors will be chosen from data tables in the proceeding sections.

| Parameter  | Value  |
|--|--------|
| $\rho_a$ -Air density, kg/m <sup>3</sup>                 | 1.225  |
| $D$ -Diameter, m   | 80     |
| $A$ -Area, m <sup>2</sup>                                | 5 027  |
| $P_r$ -Rated power, MW                                   | 2      |
| $\lambda$ -Tip speed ratio                               | 5      |
| $V_r$ -Rated wind speed, ms <sup>-1</sup>                | 15     |
| $V_t$ -Rotor tip speed, ms <sup>-1</sup>                 | 70     |
| $V_d$ -Design wind speed, ms <sup>-1</sup>               | 10     |
| $\lambda_d$ -Design (optimum) tip speed ratio            | 7      |
| $V_{ex}$ -Extreme wind speed, ms <sup>-1</sup>           | 55     |
| Nominal rotational speed, rpm                            | 16.7   |
| $\omega$ -Nominal rotational speed, rads/s               | 1.75   |
| $V_D$ -Design wind speed at max $C_p$ , ms <sup>-1</sup> | 10     |
| $C_{pmax}$ -   | 0.44   |
| $C_p$ at $V_r$   | 0.192  |
| $S$ -Solidity  | 6.5    |
| $C_D$ -Drag coefficient                                  | 1.35   |
| $H$ -Height, m   | 60/85  |
| $t$ -Blade thickness ratio, %                            | 15     |
| $Q_r$ -Rated torque kNm                                  | 1264.  |
| $T_{ex}$ -Extreme thrust kN                              | 590    |
| $D_t$ - Tower top diameter, m                            | 2.3    |
| $D_{tb}$ - Tower bottom diameter, m                      | 4      |
| Turbine diameter/tower thickness ratio                   | 250    |
| Gear ratio   | 1:92.5 |

**Table 5.6 Summary of major parameters and design driver values for the 2 MW reference turbine**

### 5.4.3 Modelling 2 MW Reference Turbine Component Weights

#### 5.4.3.1 Introduction

The weights of individual components and subsystems are modelled to Level III disaggregation given in Table 5.1 using the method summarised in Figure 5.9. The major parameters in Table 5.6 are used for the weight estimation models. The weight estimation models for the majority of the components are based on the Sunderland model, and a few on the NREL model (Fingersh, 2006; Hau, 2006; Maples, Hand et al., 2010).

### 5.4.3.2 Rotor Blades

Blades are the only major wind turbine component designed and manufactured uniquely for wind energy applications. The rotor, made up of the blades and the hub and the pitch mechanism makes a substantial part of the cost of MW turbine in terms of capital cost. The ideal material for blades will combine high strength to weight ratio and other necessary structural properties like fatigue and stiffness together with low cost (Burton, Sharpe et al., 2002). The blades for the 2 MW reference turbine are made from glass fibre reinforced polymer (GFRP). Carbon based composites have higher strength and are less dense thus making them more favourable for larger turbines.

The blade is divided into divided into 3 parts with different design drivers:

- i. Aerofoil Cladding or the shell is the working surface and has a smooth aerofoil section
- ii. The Spar is the load bearing element which supports the shell. This is assumed to be a box in the shell (aerofoil cladding). It carries the aerodynamic load exerted on the blades
- iii. Blade root flange which connects the spar to the hub. It transfers rotational torque and rotor thrust to the hub

#### i Spar model

The spar is modelled based on the Foolings and Milborrow models (Harrison, Hau et al., 2000). The mass of the spar depends on the following 4 factors and is given in equation 5.9.

1. Blade material properties- admissible stress and density
2. Aerodynamic properties  $V_r/V_d$  and design tip speed ratio  $\lambda$
3. Relative profile thickness  $t$
4. Rotor diameter

$$W_{BS} = 8.5 \times 10^{-2} F_{CL} F_{RC} \rho_a V_d^2 \lambda_m^2 \left[ \frac{1+t}{t} \right] \left[ \frac{\rho_{sp}}{\sigma_{sp}} \right] \left( \frac{D}{2} \right)^3 \quad 5.9$$

Where  $\rho_{sp}$ ,  $\sigma_{sp}$  are density and admissible strength of spar material and  $\lambda_d$  is the design tip speed ratio.  $F_{CL}$  and  $F_{RC}$  are the service factors. The  $\lambda_d^2$  term implies those blades designed to operate at high tip speed have heavy spars. Most commercial turbines use Glass fibre reinforced plastic (GFRP) material for the blades and some use fibre glass reinforced epoxy. The move towards larger MW turbines is resulting in interest in carbon fibre blades which though more expensive have higher strength and the blades can be designed to be slender reducing the blade weight. The service factors affecting blade spar design are blade flexibility, control type whether stall or pitch regulated and operational strategy whether fixed speed or variable speed.

### Blade Service factors

The values used for the service factors applied in this thesis are based on the Van Holten Model (Harrison, Hau et al., 2000). The cyclic load factor  $F_{CL}$  allows for fatigue characteristics of different blade and hub designs. Rigid blades attached to a rigid hub suffer most fatigue. Rigid hubs have all major parts fixed relative to the main shaft and they are the most common design for modern commercial 3 bladed design. Teetering allows relative motion between the part that connects to the blades and that which connects to the shaft. Teeter hubs reduce blade and hub fatigue, they are necessary in one bladed and 2 bladed designs (Manwell, McGowan et al., 2002). For the choice of the cyclic load factor, rigid hub and flexible blades that reduce fatigue are considered.

| Hub Type | Blade Type | $F_{CL}$ |
|----------|------------|----------|
| Rigid    | Rigid      | 1        |
| Rigid    | Flexible   | 0.70     |

**Table 5.7      Cyclic Load Factor for blade design**

**Rotor Control Factor  $F_{RC}$**  - This allows for the effect of the control strategy, both power and speed control. Fixed speed result in greater blade loading than variable speed. The 2 MW reference turbine has a pitch controlled variable speed system.

| Control Type             | Rotor Speed | $F_{RC}$ |
|--------------------------|-------------|----------|
| Full span variable pitch | Fixed       | 1.00     |
| Stall                    | Fixed       | 0.85     |
| Full span variable pitch | Variable    | 0.80     |

**Table 5.8 Rotor Control Factor for blade design**

## ii) Blade Aerofoil model

The blade total mass also includes the no load carrying part, the shell or the cladding. The assumption is that all the stress due to static and fatigue loads is carried by the spar and the function of the shell is to provide the lifting surface through its aerodynamic centred design. The shape and quality are therefore more important than the strength. Some new designs have quite integrated spars and shells. The weight is obtained by estimating the surface area of the glass fibre reinforced plastic (GFRP) together with the aerofoil specific weight per unit area. This is dependent on the blade area which in turn is dependent on the solidity, as well as the blade thickness and the diameter of the blade. Its service factor depends on the material used for the blades.

$$W_{BA} = 30F_A[1 + t]S\pi \frac{D^2}{4} \quad 5.10$$

Where  $S$  is the solidity and  $t$  is the blade thickness. Aerofoil weight factor  $F_A$  adjusts the weight to allow for different materials.

| Aerofoil material          | $F_A$ |
|----------------------------|-------|
| Glass reinforced polyester | 1.0   |
| Glass reinforced epoxy     | 0.6   |

**Table 5.9 Aerofoil Weight Factor for blade design**

Carbon fibre is more expensive than glass fibre, but allows the manufacture of slim blades with reduced material weight. A comparison study made between carbon fibre blade (CFRP) and the lightest glass fibre blade (GFRP) of LM 61.5P GRP for a blade length of 51.5m gave an estimated total carbon fibre blade at 7 tonnes as compared to the GFRP 17.7tons (Carlsson, Wörn et al., 2009).

### iii) Blade connection model

The connection between the blade and hub is a demanding design challenge. Blades are made of composite materials whereas the hub is made of cast steel. Bending loads have to be transmitted from the blade to the hub in the absence of substantial concentration of stress leading to crushing of the blade material. This is also complicated by the fact that the rotor is subject to extremely high dynamic loading and rotor forces are concentrated around the areas of the blade root and the rotor hub. The main types of connection are bolting to steel inserts in the GRP blade or a flange connection. The Sunderland model assumes a flange connection whereas the V80 model has steel inserts between the blades and the hub.

There are different kinds of flange connections but in most conventional GFRP blades the flange is made of steel that is sandwiched within the blades. A lightweight flange exists for glass epoxy designs, which makes use of cross bolts of the very lightweight aluminium flanges bonded into the structure as in designs by the manufacturer Enercon (Enercon, 2012). For an initial model it is assumed the root flange is made out of conventional steel and the design is driven by the thrust load on the blade at rated power.

$$W_{BC} = 2.1 F_{BC} \left[ \frac{\rho_{BC}}{\sigma_{BC}} \right] T_{ex} D^{0.7} B \quad 5.11$$

Where  $\rho_{BC}$  and  $\sigma_{BC}$  are density and admissible strength of blade connection material and  $B$  is the number of blades.  $T_{ex}$  is the extreme thrust and  $D$  is the diameter from Table 5.6. The blade connection factor  $F_{BC}$  takes into account changes affected by the control method and other improvement factors.

| Control Method and blade type            | $F_{BC}$ |
|--|----------|
| Full Span Pitch Control (conventional)   | 1.0      |
| Full Span Pitch Control (advanced blade) | 0.5      |
| Fixed Hub, rigid blades, stall control   | 0.14     |
| Teeter hub or flexible blades            | 0.1      |

**Table 5.10 Blade Connection Factor for blade flange design**

A blade connection factor  $F_{BC}$  is used to account for the modern insert connections

It is assumed the manufacturer buys material and makes the blades in a specialised blade factory as is the case with Vestas. The other option is that the manufacturer buys blades from another company. The blade cladding is usually produced in two shells using the pre-peg method (Gamesa, 2009). The two shells are then glued together with the spar in-between to form a unit.

#### 5.4.3.3 Hub Structural Weight

The weight of the hub is calculated by assuming that each of the 3 arms on the hub is a simple cantilever with the blade root momentum acting at its outer end and the inner end rigidly supported.

$$W_{HS} = 42F_{HG}F_{HL}F_{HC}\rho_a V_R^2 S D^3 \left[ \frac{\rho_H}{\sigma_H} \right] \quad 5.12$$

Where  $\rho_H$  and  $\sigma_H$  are density and admissible strength of the hub material.

The hub structural weight is a strong function of the diameter mainly because of the torque cubic dependence on  $D$ . The hub casing size and complexity vary with number blades as represented by the hub geometry factor shown in Table 5.11. The hub size and weight also depends on the power control method as it accommodates the machinery. Pitch controlled hubs would be heavier than stall controlled hubs.

| Hub Load Factor                             | $F_{HL}$ |
|---|----------|
| 3 Blades rigid hub                          | 1.00     |
| 2 Blades teeter Hub                         | 0.75     |
| 3 Blades with rigid hub and flexible blades | 0.75     |
| Hub Geometry Factor                         | $F_{HG}$ |
| 3 Blades                                    | 1.00     |
| 2 Blades                                    | 0.75     |
| Control Type Factor                         | $F_{HC}$ |
| Full-Span pitch control                     | 1.00     |
| Stall Control                               | 0.83     |

**Table 5.11 Hub Service Factors**

#### 5.4.3.4 Blade Pitch Mechanism and Bearings

The pitch mechanism is included only in full span pitch controlled machines only. The model for the hub weight is complex, and is simplified to:

$$W_{PM} = 0.11 \left[ (W_B B + 57 B M_B) \left( \frac{\rho_s}{\sigma_s} \right) \right] \quad 5.13$$

Where B is the number of blades,  $W_B$  is the blade mass and  $M_B$  is the blade moment,  $\rho_s$  is the density of steel and  $\sigma_s$  is the admissible strength of steel.

#### 5.4.3.5 Low Speed Shaft and Bearings

The main shaft which is the low speed shaft is calculated from first principles for a rotating shaft under an applied bending moment. To estimate the weight, the main dimension is the shaft diameter ( $d_0$ ) that fulfils the strength conditions over its working lifetime. This is given by:

$$d_0 = \sqrt[3]{19.6 \left[ \left[ \frac{Q_{LSS}}{\sigma_{LSS}} \right]^2 + \left[ \frac{M_{LSS}}{\sigma_e} \right]^2 \right]^{1/2}} \quad 5.14$$

Where  $\sigma_y$  is the yield stress of the shaft material and  $\sigma_e$  is the endurance.  $Q_{LSS}$  is the rated torque on the shaft multiplied by a safety factor of 3.  $M_{LSS}$  is the design bending moment on the shaft multiplied by a safety factor of 1.25.

$$M_{LSS} = 0.25 L_{LSS} g W_{ROT} \quad 5.15$$

The weight of the rotor  $W_{ROT}$  is calculated up to the flange connection between the hub and the low speed shaft. The length of the moment arm is assumed to be 1/5 of the shaft length  $L_{LSS}$ , and  $g$  is the acceleration due to gravity.

$$L_{LSS} = 0.005 F_{LSS} g D \quad 5.16$$

The low speed shaft factor  $F_{LSS}$  is dependent on the drivetrain arrangements.



| Drivetrain Type | $F_{LSS}$ |
|-----------------|-----------|
| Modular         | 1.0       |
| Short           | 0.4       |

**Table 5.12 Low Speed Shaft Factor**

The weight is calculated from the shaft's volume and density of steel, the shaft material.

$$W_{LSS} = A_{LSS} L_{LSS} \rho_{LSS} \quad 5.17$$

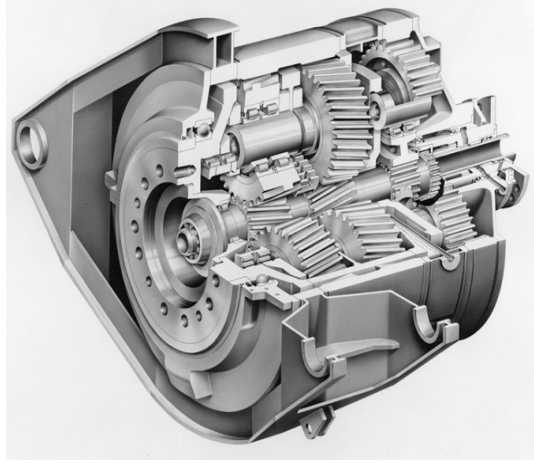
Some shafts are hollow to allow pitch signals or pitch controls to be passed into the hub, and tapered to reduce material cost. The low speed shaft bearings allow rotor weight and rotor thrust to be transferred onto the nacelle bedplate. They reduce shear loads on the gearbox input shaft. Positioning of the bearings along the shaft is an important design decision. Bearings are usually standard components, but with the trend toward MW turbines, manufacturers are moving towards designing turbine specific bearings. The leading global supplier of bearings, SKF have designed a specialised bearing for the REpower 5 MW turbine. The 2006 turbine design had a 1.5 m diameter rotor shaft supporting the 130 tonne 3 bladed rotor. The designed bearing with an inner diameter of 1.5 m weighed 2700 kg (SKF, 2007).

The bearing mass is modelled here using the NREL model given in Equation 5.18. The mass of the housing is assumed to have the same weight as the bearing (Fingersh, 2006).

$$W_{BRNS} = ((0.0133D - 0.3333) * 0.0092D^{2.5}) \quad 5.18$$

#### 5.4.3.6 Gearbox

Gear trains have 2 distinct types: parallel (spur) and epicyclic (planetary). Parallel are bulky heavy and inexpensive and useful for high speed and low torque purposes whereas planetary are compact and lightweight and are mainly used for low speed and high torque purposes. Figure 5.10 is an example of a typical gearbox for a 2 MW turbine



**Figure 5.10** Three-stage planetary gearbox of the 2 to 3 MW power class (Hau 2006).

Although gearboxes are a standard component for the turbine, their function is opposite to the conventional. Most gearboxes are designed to step-down from high speed low torque to low speed high torque operating under full load conditions whereas for wind turbines, the gearbox steps up from low speed high torque to high speed low torque.

Typically, commercial turbines have 2 or 3 stages with most MW turbines gearboxes having 3 stages in a combination of spur and planetary gears. To estimate the total gearbox weight, the weight of the different stages has to be estimated. There are different arrangements of the spur and planetary gear combinations giving different step-up ratio. A gearbox combination with all planetary gears gives the highest ratio. The ratio for each stage  $U_s$  is an important parameter for the gearbox design and the product of the three stages gives the overall gearbox ratio  $U_0$ . The 2 MW reference turbine has an overall gear ratio of 1:92.8. The weight of the gearbox in each stage ( $W_{GSN}$ ) is dependent on its ratio and the type of the gear either planetary or spur.

$$W_{GSN} = 3.2Q_s \frac{F_s F_W}{F_{GD}} \quad 5.19$$

Where  $Q_s$  is the output torque at that particular gear stage. The service factor  $F_s$  depends on the control type of the wind turbine.

| Control Type             | Rotor Speed | Gearbox Service Factor $F_S$ |
|--------------------------|-------------|------------------------------|
| Full-span variable pitch | fixed       | 1.75                         |
| Stall                    | fixed       | 2.00                         |
| Full-span variable pitch | variable    | 1.25                         |

**Table 5.13 Gearbox Service Factors**

The other factors  $F_{GD}$  and  $F_W$  are derived from standard gear design.  $F_{GD}$  represent material and surface finish effects and  $F_W$  expresses the relationship between gear stage ratio and the relative volume of that stage. The 2 MW reference turbine has epicyclic gears for stage 1 and stage 2 and spur gear for stage 3.

For the spur gear in the third stage the gearbox weight factor is estimated from:

$$F_W = 1 + \frac{1}{U_S} + U_S = U_S^2 \quad 5.20$$

Where  $U_S$  for the spur gear = 2.5. For epicyclic gears in the first and second stage,

$$F_W = \frac{1}{Z} + \frac{1}{[ZU_{SN}]} + U_{SN} + U_{SN}^2 + 0.4 \frac{[1 + U_{SN}]}{Z} [U_S - 1]^2$$

$$F_W = \frac{1}{Z} + \frac{1}{[ZU_{SN}]} + U_{SN} + U_{SN}^2 + 0.4 \frac{[1 + U_{SN}]}{Z} [U_S - 1]^2 \quad 5.21$$

Where  $Z$  is the number of planet wheels in a stage, depending on the stage ratio and in this case  $U_S = \sqrt{(U_o/2.5)} = 6.09$  for the 2 MW reference turbine.  $U_{SN}$  is another ratio for the planetary gears which the sun wheel ratio is given by

$$U_{SN} = \left[ \frac{U_S}{2} \right] - 1 \quad 5.22$$

Table 5.14 summarises the results for the gearbox model.

| Gearbox Stage     | $U_s$ | Stage rpm | Torque $Q_s$ (kNm) | $F_{GD}$           | $F_s$ | $F_w$ | Weight (kg) |
|-------------------|-------|-----------|--------------------|--------------------|-------|-------|-------------|
| Stage 1 Epicyclic | 6.09  | 10.66     | 188                | $1.75 \times 10^3$ | 1.25  | 16.28 | 12 305      |
| Stage 2 Epicyclic | 6.09  | 64.90     | 31                 | $1.75 \times 10^3$ | 1.25  | 16.28 | 2 564       |
| Stage 3 Spur      | 2.50  | 162.26    | 12                 | $1.75 \times 10^3$ | 1.25  | 10.15 | 101         |

**Table 5.14 Gear stages model results**

The first stage gear is the heaviest because of the high torque and slow speed. The total gearbox weight is the summation of the stage gears' weights.

#### 5.4.3.7 Ancillary Mechanical Equipment

The majority of ancillary mechanical components are small items difficult to model and differences in the type of equipment exist for different turbine models. However, they generally have rated power as their design driver. It is assumed that the weight of mechanical equipment is 5% of the total towerhead weight (Harrison, Hau et al., 2000).

The mechanical brake weight is obtained from the sum of the weights of the brake callipers, weight of brake disc and the hydraulic pack. This usually accounts for less than 1% of the towerhead weight if it is placed on the high speed shaft and heavier around 2% if placed on the low speed shaft (because of the high torque). The design driver for the high speed shaft and coupling is the low torque transmitted to the generator. This is the rotor torque reduced in proportion to the overall gearbox ratio. The design driver for the lubrication and hydraulic systems is the power rating. Air conditioning is necessary for areas that have hot or cold climates. Fire equipment is installed in case of such an incident in the nacelle. Both systems are driven by the nacelle volume.

#### 5.4.3.8 Electrical Generator

##### Squirrel Cage Induction Generator

The induction generator weight is modelled as:

$$W_{GN} = F_{G1}P + F_{G2} \quad 5.23$$

Where  $F_{G1}$  and  $F_{G2}$  are calibration coefficients which depend on generator speed and  $P$  is the rated power.

| Generator Speed rpm | $F_{G1}$ | $F_{G2}$ |
|---------------------|----------|----------|
| 1000                | 4.50     | 41       |
| 1500                | 3.13     | 418      |

**Table 5.15 Induction Generator Calibration**

### Synchronous Generator

The weight for a synchronous generator is estimated using equation 5.24.

$$W_{SG} = 14.86P^{0.75} \quad 5.24$$

### Double Fed Induction Generator (DFIG)

A standard squirrel cage induction generator for the 2 MW turbine was estimated at 6.678 tonnes. Using the NREL model the generator weight is estimated at 7.17 tonnes. A factor of 0.82 is used for the DFIG in agreement with previous studies to give a DFIG weight of 5.50 tonnes (Polinder, Van Der Pijl et al., 2006; UPWIND, 2012).

#### 5.4.3.9 Power Electronics Converter

The weight of the 30% partial converter for the DFIG generator system was obtained from results of previous studies (Bywaters, John et al., 2005; Polinder, Van Der Pijl et al., 2006; UPWIND, 2012).

#### 5.4.3.10 Electrical equipment and power cables

Additional electrical equipment for the turbine equipment includes switchgears and power factor correction capacitors, transformers and control cabinets. 20% of the weight is located in the turbine and 80% at ground level in the tower unless the transformer is located in the nacelle. Power cables run from the nacelle (generator) to the equipment at the base of the tower. Design drivers for the cable are cable length,

generator voltage and current carried. Specific weight can be found from manufacturers' data. It is assumed all electrical equipment has rated power as the main design driver.

#### 5.4.3.11 Nacelle

##### Nacelle Bedplate

The weight of the bedplate or the main frame is the sum of the steel required to withstand the rotor torque  $W_{BPQ}$ , the rotor thrust  $W_{BP THR}$ , the rotor weight  $W_{BPRWT}$  and to provide the required bedplate area for all the components  $W_{BP AREA}$  (Maples, Hand et al., 2010).

Total weight of nacelle bedplate is given by:

$$W = W_{BPQ} + W_{BP THR} + W_{BPRWT} + W_{BP AREA} \quad 5.25$$

The main service factor is the bedplate weight factor  $F_{BP}$  and it is dependent on the drivetrain design. It has a value of 1 for a standard drivetrain type and 0.5 for a short one such as a compact direct drive drivetrain.

##### 1. Bedplate weight due to rotor torque.

$$W_{BPQ} = 8.8 \times 10^{-3} F_{BP} Q_r \quad 5.26$$

Where  $Q_r$  is the rated torque estimated in section 5.4.2.

##### 2. Bedplate weight due to rotor thrust

This is calculated from the bending moment produced by the extreme thrust  $T_{ex}$  and assuming that the height of the shaft above the bedplate is a function of the tower top diameter  $D_t$ .

$$W_{BP THR} = 4.4188 \times 10^{-3} F_{BP} T_{ex} D_t \quad 5.27$$

### 3. Bedplate weight due to rotor weight

The design driver is assumed to be solely bending moment caused by the rotor weight  $W_{ROT}$  and that the moment due to other drivetrain components is balanced by the tower central line and the low shaft weight is balanced by the generator and ancillary equipment weight moment.

$$W_{BPRWT} = 4.29 \times 10^{-2} F_{BP} W_{ROT} D_t \quad 5.28$$

### 4. Bedplate weight due to area

The bedplate area,  $A_{BP}$  is calculated giving allowance for maintenance.

$$W_{BPAREA} = 100 F_{BP} A_{BP} D_t \quad 5.29$$

The bedplate is assumed to be a rectangle of length  $L_{BP}$  and width  $0.5L_{BP}$ . The area is thus given by:

$$A_{BP} = \frac{L_{BP}^2}{2} \quad 5.30$$

$$L_{BP} = 8.3 \times 10^{-2} F_{DR} D_t \quad 5.31$$

The bedplate drivetrain factor  $F_{DR}$  adjusts lengths for different drivetrain types. For a standard drivetrain such as that for a DFIG reference turbine it has a value of 1 and 0.8 for a short drivetrain such as the direct drive (DD) drivetrain (Harrison, Hau et al., 2000).

### Nacelle Cladding Weight

The nacelle cladding protects equipment and maintenance crew in all weathers. It is normally made out of glass fibre reinforced polymer (GFRP) material and its weight is a function of volume enclosed. The nacelle cladding area is estimated using Equation 5.32.

$$A_{NCLAD} = 2L_{BP}^2 \quad 5.32$$

And the weight of the GFRP shell including stiffeners and frames is given by

$$W_{NCLAD} = 84.1A_{NCLAD} \quad 5.33$$

#### 5.4.3.12 Yaw System

The yaw mechanism keeps the turbine pointing in the wind direction so as to maximize energy capture, and its weight is calculated using equations 5.34.

$$W_{YAW} = 10^{-3}F_{YAW}[[0.4W_{AYAW}D] + [0.975T_R D_t]] \quad 5.34$$

$W_{AYAW}$  is the sum of weights of all components above the yaw,  $T_{ex}$  is the rotor thrust,  $D$  is the rotor diameter and  $D_t$  is the tower top diameter. The yaw factor  $F_{YAW}$  depends on the number of blades and is 1 for 3 bladed turbines.

#### 5.4.3.13 Tower

Towers are typically made of steel, though concrete ones exist. Most commercial turbines are tubular though a significant number are lattice. For tubular towers, the main parameters for design are the hub height, the tower radius and the tower wall thickness. The tower mass is a function of these and is given by:

$$W_{TOW} = 2\pi R_t H \delta \rho_t \quad 5.35$$

Where  $R_t$  is the tower radius,  $H$  is the hub height,  $\delta$  is the tower thickness and  $\rho_t$  is the density of the tower material. For a simple soft designed with respect to buckling criterion the tower radius and the wall thickness are given by:

$$R_{t,0} = \left[ \frac{175M_{tb}}{2\pi\sigma_{tadm}} \right]^{1/3} \quad 5.36$$

$$\delta_0 = \frac{2R}{175} \quad 5.37$$

This applies for optimum design. Where  $M_{tb}$  is the tower foot bending moment and  $\sigma_{tadmin}$  is the admissible stress of the tower material. If fatigue loading is a design



driver for the tower then  $M_{tb}$  is proportional to  $D^2 H^{9/7}$ , where  $D$  is the rotor diameter and  $H$  is the hub height.

The specified tower is constructed of tubular steel and designed to withstand peak and fatigue bending moments at the base and top. It has a linear taper of diameter and a constant tower diameter/wall thickness ratio ( $d_t/\delta$ ). Fingersh (2006) uses ( $d_t/\delta$ ) of 320 whereas the Sunderland model estimates the ratio as 175 for a straight cylindrical turbine, not tapered (Harrison, Hau et al., 2000). A ( $d_t/\delta$ ) ratio of 320 is optimistic because it represents an upper practical limit. In order to save material costs, a high ratio is desirable. For d/t ratios above 320, however, towers become unstable and subject to local buckling (Fingersh, 2006). It is proposed to use 250 to give a thickness of 20 mm at the base. Additionally, the diameter at the top is constrained to be at least  $\frac{1}{2}$  of the base diameter. The structural steel used has a yield strength of 350 MPa.

Practically, the tower is manufactured and transported in sections and then assembled on site through flange connections. Steel plates are cut and are shaped into cylindrical rings of different sizes by passing them through a machine with large rollers. The rings are welded into sections that can be transported. The number of rings per section is dependent on the model and required height. Typical rings have a height of around 20 m. The sections are painted for aesthetics and for protection against corrosion. The other auxiliary components such as platforms and ladders are mounted onto the sections insides.

#### 5.4.4 Components Weight Results

Table 5.16 summarises the results for the individual weights of different components and their contribution to the total weight.

| Components                          | Weight (tonnes) | Service Factors and Values Comments   |
|-------------------------------------|-----------------|---|
| <b>Blades</b>                       |                 | Glass reinforced polyester. flexible blades and fixed hub   |
| Spar                                | 3.56            |   |
| Aerofoil Cladding                   | 2.42            | $F_{CL} = 0.7, F_{RC} = 0.8$  |
| Blade Connection                    | 0.78            | $F_A = 1, F_{BC} = 0.4$   |
| Total Each blade                    | 6.76            |   |
| <b>Hub</b>                          | 15.76           | $F_{HL} = 0.75, F_{HG} = 1$<br>$F_{HC} = 1, F_{BC}$   |
| <b>Pitch Mechanism</b>              | 3.18            |   |
| <b>Low Speed Shaft</b>              | 4.42            | $F_{LLS} = 1, d_0 = 0.565\text{m}, L_{LLS} = 4\text{ m}, M_{LLS} = 191\text{ kNm},$<br>$Q_{LLS} = 3,429\text{ kNm}$   |
| <b>Bearing System</b>               | 1.09            | NREL model. Housing weight equal to bearing weight  |
| Bearing                             | 0.54            |   |
| Gearbox                             | 15.70           | $F_S = 1.25, F_{GD} = 1.75$   |
| Mechanical Equipment                |                 | Assumed 5% of the towerhead weight for the 2 MW reference turbine.  |
| DFIG Generator                      | 5.50            | Factor of 0.82 for conventional IG  |
| Electrical equipment + cables       | 7.78            | NREL model  |
| Power electronics                   | 1.00            | Upwind  |
| Nacelle bedplate                    | 26.09           | $W_{BPQ} = 10.06\text{ tonnes}, W_{BTHR} = 6.132\text{ tonnes}, W_{BPRWT} = 3.595\text{ tonnes},$<br>$W_{BPAREA} = 6.292\text{ tonnes}$<br>$F_{BP} = 1, F_{DR} = 1$<br>$L_{BP} = 6.64\text{ m}, A_{BP} = 22\text{ m}^2$ |
| Nacelle Cladding                    | 7.40            | $A_{NCLAD} = 88\text{ m}^2$   |
| Yaw System                          | 4.24            | $F_{YAW} = 1$   |
| Tower:                              |                 |   |
| $H = 60\text{ m}$                   | 128.00          | $\delta_0 = 0.02\text{ m}, d_t = 2.30\text{ m}, d_b = 2.4\text{m},$   |
| $H = 85\text{ m}$                   | 153.00          |   |
| <b>Total Turbine Weight</b>         |                 |   |
| <b><math>H = 60\text{ m}</math></b> | <b>243.00</b>   |   |
| <b><math>H = 85\text{ m}</math></b> | <b>268.00</b>   |   |

**Table 5.16 Turbine Components Weight Results Modelling for the 2 MW reference turbine based on Sunderland Model (Harrison, Hau et al., 2000).**

## 5.5 Discussion

The main characteristic of an engineering based detailed assessment is the bottom-up approach whereby a system is disaggregated so as to assess individual components where possible. High levels of disaggregation imply complex models and high resource requirements, therefore, a balance is needed when separating components. The disaggregation of the 2 MW reference turbine and subsystems was guided by the form in which the components are supplied to the turbine manufacturer.

The engineering assessment modelling approach was chosen so that it would allow the development of models for the components at the greatest possible levels of

detail whilst avoiding complexity associated with detailed costing models. Additionally, the need to develop methods and reference turbine results that would be further used or upgraded favoured the use of the Sunderland model. NREL studies used the model to analyse the impact of upscaling turbines on cost of wind energy.

The modelling approach was found to be dependent on reliable reference values for the turbine. The choice of the reference turbine and its definitive parameters is a crucial process when developing generic models. A lot of input data is required for detailed engineering assessment and with the unavailability of data in the public domain, modelling is based on making a number of assumptions.

The Sunderland model approach was found to be the most ideal for the detailed analysis of the wind turbine. Costing is related to weight and unlike cost data, weight data can be made available and if not can be derived using theory. Manufacturers can readily provide the weight of some components, or better still, of the whole turbine. Physical attribute data is not as confidential as cost data and where the former is limited, engineering design laws can be used to estimate any missing parameters.

The detailed modelling has an important role therefore, in providing alternative methods where data that would normally be available from manufacturers or developers is limited. It allows costing major components in relatively simple ways. For example, the generator was considered as a component whose weight is estimated using one mathematical model. However, the generator is made up of different subcomponents with different materials such as iron, copper and laminations (Polinder, Van Der Pijl et al., 2006). The simplification to one model for the generator reduces the complexity, and the use of matching factors in the established Sunderland model mathematical equations improves the validity of the results.

The Sunderland model was found to suffice and the results were compared with those that exist in literature. Table 5.17 compares the results for the 2 MW reference with a diameter  $D=80$  m and height  $H=85$  with those from the Vestas V80 manufacturer's brochure, NREL studies' results and other relevant studies.

| Component                   | 2 MW Reference Turbine ( $D=80$ m, $H=85$ m) | Vestas <sup>1</sup> V80 ( $D=80$ m, $H=80$ m) | NREL <sup>2</sup> 1.5 MW ( $D=70$ m, $H=65$ m) | NREL <sup>2</sup> 3 MW ( $D=90$ m, $H=80$ m) | Database <sup>3</sup> and other sources ( $D=85.5$ m, $H_{av}=87.7$ m) |
|-----------------------------|--|---|--|--|--|
| Blades                      | 20.1   | 19.5  | 13.8   | 28.8   | 19.2, 20.7 <sup>5</sup>  |
| Hub                         | 15.8   | 18.0  | 10.8   | 15.8   | 18.0   |
| Pitch Mechanism             | 3.2  |   | 3.6  | 6.2  |  |
| <b>Rotor</b>                | <b>39.1</b>                                  | <b>37.0</b>                                   | <b>28.3</b>                                    | <b>51.0</b>                                  | <b>38.7</b>  |
| Shaft                       | 4.4  |   | 3.0  | 6.3  |  |
| Bearings                    | 1.2  |   | 0.7  | 1.7  |  |
| Gearbox                     | 15.7   |   | 10.2   | 21.0   | 8.5 <sup>6</sup>   |
| Generator                   | 5.1  |   | 5.5  | 10.4   | 5.3 <sup>6</sup> , 5.3 <sup>7</sup>                                    |
| Auxiliary Equipment         | 9.8  |   | 0.1  | 0.3  |  |
| Nacelle Frame               | 26.1   |   | 19.8   | 40.4   |  |
| Nacelle Cover               | 7.4  |   | 2.4  | 4.3  |  |
| Yaw Mechanism               | 4.2  |   | 1.9  | 4.3  |  |
| <b>Drivetrain + Nacelle</b> | <b>76.2</b>                                  | <b>69.0</b>                                   | <b>43.6</b>                                    | <b>88.6</b>                                  | <b>68.2</b>  |
| <b>Tower</b>                | <b>153.0</b>                                 | <b>148.0<sup>8</sup></b>                      | <b>98.0</b>                                    | <b>201.0</b>                                 | <b>137.0 - 204.0</b>   |
| <b>Turbine Weight</b>       | <b>268.0</b>                                 | <b>254.0</b>                                  | <b>169.0</b>                                   | <b>340.0</b>                                 | <b>261.0 - 340.0</b>   |

**Table 5.17 Validation of Component Weight Results (Values in tonnes)**

1. Vestas data from manufacturers brochures (Vestas, 2012) and windfarm projects.
2. NREL results from the Scaling models derived from the Sunderland model. The 3 MW turbine was designed for offshore purpose (Fingersh, 2006).
3. The weights are based on a database of 2 MW turbines on the market as published by manufacturers. The averages are given for 27 2 MW turbine models 11 manufacturers on the Germany Wind Association websites (BWE, 2010; WEM, 2012). The values are averages for data provided by manufacturers with some providing partial data.
4. Germany database-Manufacturers supply their turbines with a range of Hub heights and the figures in the table give the range of averages for different heights
5. (Rogowsky and Laney-Cummings, 2009)
6. (Aguglia, Viarouge et al., 2009)
7. (Polinder, Van Der Pijl et al., 2006)
8. Based on a Vestas V80 turbine with a tower height  $H = 80$  m.

The turbine tower is the heaviest component or subsystem, making up over 50% of the total turbine weight. The tower is manufactured from steel, and this results in steel being the major raw material for wind turbines. The tower however, is not a complex component to manufacture and will not likely have such a great share of cost.

Generally, the modelled costs are within the range of values from NREL models, the Vestas V80 weight values, and the average values from database of commercial 2 MW turbines. The major difference is in the nacelle and drivetrain subsystem costs. The drivetrain is the most complex subsystem with more components compared to

the rotor and the tower. The weight of auxiliary drivetrain components including: mechanical equipment, electrical equipment, cables and power electronics for the 2 MW reference turbine might be the source of the major differences as differences in the definition of such might differ. Weight values for the drivetrain might separate some equipment such as cables and transformers from the turbine weight as some might be considered as equipment for balance of station. The Vestas brochure only gives the total drivetrain and nacelle weight and it is difficult to make a comparison without isolating the drivetrain weight. As mentioned in Section 5.4.3, the majority of these minor equipment have power rating as the main design driver of cost and the estimation of their weight might not be a priority in scaling cost models. The NREL model did not estimate the weight of most of these “minor” drivetrain components. The estimated weight of the equipment is however, significant and the model results indicate about 10% of the towerhead weight (rotor + drivetrain weight).

## 5.6 Conclusion

This chapter commenced the process of the engineering assessment of a wind turbine. The detailed analysis process involved disaggregating the wind turbine into components or subassemblies for assessment. The level of disaggregation was chosen to strike a balance between the benefits of capturing detailed data for the intended purposes and avoiding complexity that comes with excessive disaggregation which result in numerous components to be modelled. The 2 MW reference turbine was chosen for the engineering assessment based on the commercial Vestas 2 MW turbine to assist in choosing relevant system parameters for the estimations. The assessment models developed for the quantitative analysis were based on the commonly used Sunderland Model (Harrison, Hau et al., 2000).

The initial process of the detailed model which was addressed in this chapter involved estimating the weight of the components and using models that derived the physical structure of the components based on the component loadings. The models also included service factors dependent on the way of operation and matching factors to match to real life cases. Where the Sunderland model was limited, weights were derived from relevant studies. The results were compared with weight estimations for

the NREL studies which were also based on the Sunderland model, the Vestas brochure for subsystem weights for the V80 model and other relevant sources. The majority of the results for the 2 MW Reference Turbine weight were found to be in range with these sources. Discrepancies were found in the drivetrain, a complex subsystem with many components. Particularly, significant differences were in the results of the minor electrical and mechanical equipment. A possible explanation is the differences in the definition of the auxiliary equipment.

Although a linear relationship exists between weight and cost, weight estimations on their own cannot be used to draw economic conclusions for a complex system such as wind turbine consisting of several components exhibiting differences in materials and complexities. To complete the detailed assessment of the 2 MW Reference turbine, the costs of the turbine components need to be estimated according to the relationships which exist between each component's weight and cost. The cost assessment of the 2 MW reference turbine and the other cost components for onshore wind energy technology is the focus of the next chapter.

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## **6 2 MW Reference Turbine Cost of Energy Estimation**

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### **6.1 Introduction**

In this chapter wind energy costs are estimated for the 2 MW reference turbine using engineering costing methods. The focus of this chapter is to estimate wind turbine costs, installed capital costs (ICC) and ultimate cost of energy (COE), the primary metric for measuring the cost of wind energy. The turbine weight results of the detailed assessment from the previous chapter are used to estimate the cost of the 2 MW reference turbine.

The aim is to ensure that the models of the engineering assessment of the reference turbine are upgradeable for purposes of analysing the impact of technological improvements in the subsequent parametric model, so that the results can ultimately be integrated into learning curve analysis in the chapter 8.

Section 6.2 describes the costing of wind energy and the calculation of COE. Section 6.3 estimates the cost of turbine and its components using the results of the weights of the components from the last chapter. Section 6.4 estimates the ICC by adding the BOS to the turbine capital costs. Section 6.5 estimates the annual (O&M) costs and section 6.6 describes the project finance cost. The turbine performance in the form of the annual energy production (AEP) is estimated in section 6.8. Section 6.9 gives the COE results and a sensitivity analysis is used to analyse the impact of the cost components on the COE. The results are also compared to cost estimates data from reports and relevant studies. Section 6.9 is a discussion of the chapter and section 6.10 concludes this chapter.

### **6.2 Costing Wind Energy**

As a renewable source of energy, wind energy has no fuel costs, but it is highly capital intensive. Cost of energy (COE) provides a holistic single metric that

describes energy technology cost in a way that allows comparisons across energy technologies and across countries (Lantz, Wiser et al., 2012). COE is levelised over the lifetime of the project hence the term “levelised cost of energy” (LCOE) is often used. The annual costs of the wind energy technology are averaged over the lifetime of the turbine which is typically 20 years.

The estimation of COE is highly site specific. The wind resource at the site should be well understood and information on O&M data is necessary. The costing of installed capacity is often used for conventional energy sources and plants, but can be misleading for wind energy whose competitiveness is also hinged on the turbine performance. For example, a turbine with high rated power installed at a site with low wind speed will not achieve high yield. However, ICC is important when the site information necessary for performance calculation is limited. Moreover wind turbine designs are not totally disassociated with anticipated performance as manufacturers optimise designs for specific wind speed classes.

Estimation of the COE may require the use of reasonable assumptions where data is limited and these can be validated using previous study results and relevant data from authoritative associations and organisations such as the IEA and EWEA. Alternatively ICC, the cost of installed capacity (cost/kW or cost/MW) is used where the use of COE has limitations or is unreliable.

This study aims to estimate COE in €/MWh and use cost of installed capacity in €/MW for assessments of lesser detail such as for parametric modelling and for comparison with existing data from reports and studies. Costs in other currency such as £ and \$ are also referred to for comparison purposes. The cost of the turbine will also be used for parametric modelling purposes in chapter 7.

### **6.2.1 COE Estimation**

The main components of cost of wind energy are the following:

1. Wind turbine capital costs
2. Balance of Station (BOS) costs
3. Operation and Maintenance (O&M) annual costs

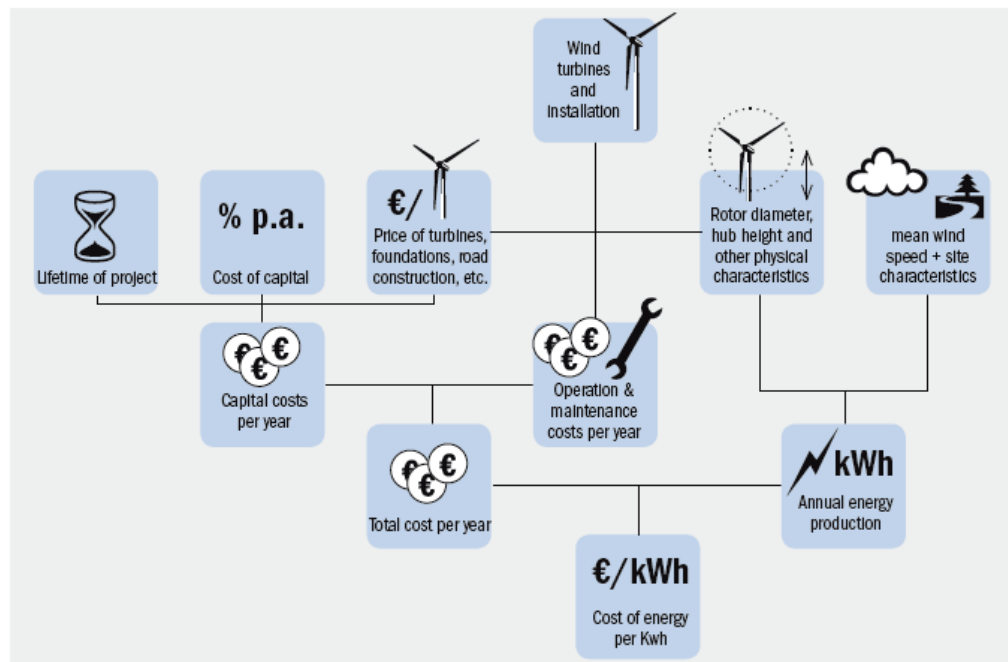


4. Project Finance Factors (Discount Factor)
5. Turbine performance, Annual Energy Production (AEP)

The sum of the wind turbine costs and the BOS costs give the installed capital cost (ICC) for the project. Equation 6.1 is used to estimate the annual COE:

$$COE = \frac{(DR \times ICC)}{AEP} + O\&M \quad 6.1$$

Where *ICC* is the installed capital cost (turbine cost + BOS) in (€), *DR* is the discount rate to account for the cost of capital over the years (%), *AEP* is the net annual energy production or the yield (MWh) and *O&M* is the annual operation and maintenance costs (€/MWh) and it includes all annual operating costs. If O&M costs are expressed in terms €/year then they will need to be divided by the AEP in equation 6.1. Figure 6.1 is a detailed representation of the cost centres for estimating the cost COE.



**Figure 6.1** Estimation of the Cost of Energy from wind (Krohn, Morthorst et al., 2009)

## **6.3 Turbine Capital Costs**

### **6.3.1 Specific Costs**

Specific cost is a unit cost representing all costs associated with producing a component from its raw materials to a finished product. Estimation of specific costs consists of calculating material, manufacturing (labour machinery, assembly) and overheads costs. A detailed approach to assessment involves capturing and modelling all cost centres so as to identify cost reduction opportunities that might be overshadowed in the overall cost. However, most wind turbine components are complex systems with a number of subcomponents with different materials that are produced using different kinds of manufacturing processes. For this work, components are considered complete as sold by turbine manufacturers' suppliers or provided by supplier departments in the case of in-house manufacturing. A representative specific cost that takes into account all of the subcomponents is used for each individual component or subsystem.

The estimation or choice of specific costs is based on the assumption that all the cost drivers of the constituent subcomponents and the assembling of such, have been taken into account. Specific costs not only represent material and manufacturing costs but market dynamics of the subcomponents. The estimation or choice of specific costs from relevant sources is therefore an important process in engineering costing. It is interesting to note that in spite of the complexity and variability of some industrial processes such as blade manufacture, there is often useful convergence of wind turbine costs with a fairly reliable average cost per kg being established at least for individual manufacturers, sometimes over a number of years (Jamieson, 2011)

Specific costs of most components in the rotor, major drivetrain components and structural components including the tower are defined as cost/weight (€/kg) whereas for some electrical and control components are more appropriately estimated as a function of the rated power and the specific cost (€/kW) is used.

Current cost data of components is hardly ever available in the public domain. Specific costs that were developed in earlier studies based on real market data are used for this study. Specific costs based on those given by Harrison (2000), NREL

studies and other relevant reports were the readily available options for the costing (Bywaters, John et al., 2005; Fingersh, 2006; Maples, Hand et al., 2010). However, there was a need to convert from currencies such as the \$ and the £ to €s and to adjust the value of the € for inflation over the years from 2000 to 2012 levels as detailed below using information from the European Central Bank (ECB) through email in 2010 (22 April 2010). The conversion of currency plays an important role in the accuracy of estimated costs.

### 6.3.1.1 Adjusting historical money to current values

To express a price from the past in a price at today's price level the idea of inflation-adjusted is used. The price value of money observed in the year 2000 is adjusted to the price level of 2012 using following calculation:

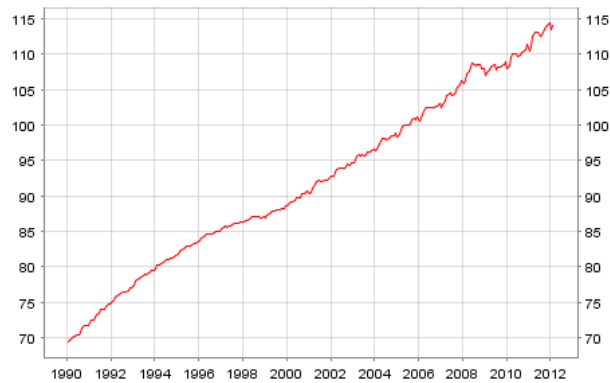
$$P_{2012} = P_{2000} \times \frac{I_{2012}}{I_{2000}} \quad 6.2$$

Where  $P_{2012}$  and  $I_{2012}$  are price and price index in 2012 and  $P_{2000}$  and  $I_{2000}$  are price and price index in 2000.

A few choices exist for the price index but most commonly, the consumer price index used in the Euro area is the harmonised index of consumer prices (HICP). The index is designed for international comparisons of consumer price inflation. It is used for the assessment of the inflation convergence criterion as required under Article 121 of the Treaty of Amsterdam and by the ECB for assessing price stability for monetary policy purposes. The ECB defines price stability on the basis of the annual rate of change of the Euro area and compiles indices on the basis of harmonized standards, binding for all Member States. In 2005 the HICP was 11.2% higher than in 2000. Table 6.1 gives the HICP values from 2000 to 2012 and Figure 6.2 is a graphical representation of the trend based on 2005 price of €100.

| Year               | Average HICP index<br>(Based on 2005 May = 100) | $I/I_{2012}$ |
|--------------------|---|--------------|
| 2000               | 89.69   | 1.259        |
| 2005               | 100.00  | 1.130        |
| 2010               | 109.84  | 1.028        |
| 2011               | 112.83  | 1.001        |
| 2011 to March 2012 | 112.96  | 1.000        |

**Table 6.1 European rate of inflation- Source European Central Bank**



**Figure 6.2 HICP index for calculating inflation for the Euro (source European Central Bank)**

### 6.3.1.2 Specific Cost Estimates

Although the 2 MW reference turbine based on the Vestas V80 model, the study maintains the aim of developing generic costing methods for different turbine ratings. Price and cost data vary depending on the manufacturer and their suppliers (Bolinger and Wiser, 2011). To account for variations in company specific factors, supplier market factors, inflation adjustments and errors in estimation, cost estimates are estimated in ranges as in other similar cost studies. Two scenarios are set, a low cost range where costs are set at lowest possible levels and high cost range where high cost assumptions are used. The cost results of the 2 MW reference turbine, ICC and COE components and ultimately the turbine ex-works cost are subsequently given as a range rather than absolute values. The turbine components specific costs reflect most of these cost variation factors and are therefore given as a range.

Harrison (2000) estimated specific costs of final components inclusive of all material, manufacturing and overhead costs. Table 6.2 gives a range of specific costs by in 2000 levels as well as converted to levels of 2012 which are used for the 2 MW reference turbine.

| Category                     | Components   | €/kg (2000) | €/kg (2012) Low cost | €/kg (2012) High cost |
|------------------------------|--|-------------|----------------------|-----------------------|
| <b>Mechanisms</b>            |  |             |                      |                       |
| Special/ Complex Mechanisms  | Tip brakes<br>Blade flange<br>Pitch mechanism              | 15-20       | 18.90                | 25.20                 |
| Standard Mechanisms          | Gearbox<br>Shafts<br>Bearings<br>Yaw bearing and mechanism | 8-10        | 10.10                | 12.60                 |
| <b>Structures</b>            |  |             |                      |                       |
| <b>Heavily loaded</b>        |  |             |                      |                       |
| Composites                   | Blades   | 8-10        | 10.10                | 12.60                 |
| GRP                          | Blades   | 10-15       | 12.60                | 18.90                 |
| GRE                          |  |             |                      |                       |
| • Steel                      | Hub  | 5-7         | 6.30                 | 8.80                  |
| Castings                     | Bedplate   | 2-5         | 2.50                 | 6.30                  |
| Fabrication                  |  |             |                      |                       |
| <b>Intermediately loaded</b> |  |             |                      |                       |
| • Fabrication                | Tower <sup>3</sup>   | 1-3         | 1.30                 | 3.80                  |
| <b>Lightly loaded</b>        |  |             |                      |                       |
| • Composites                 | Nacelle cladding   | 3-5         | 3.80                 | 6.30                  |
| <b>Total artefact</b>        | Towerhead assembly   | 10-12       | 12.60                | 15.10                 |

**Table 6.2 Cost of components manufacture (Harrison, Hau et al., 2000). Values converted using European Central Bank inflation data from Table 6.1**

The 2012 low specific costs in column 4 are estimated from the lowest specific cost in column 3 and the high costs in column 5 from the highest costs in column 3. The components are categorised according to whether the component is standard or complex, the latter being more specialised for wind turbines. The categorisation is similar to that given in Chapter 2 for cost estimating new components. Specialised components like blades and pitch mechanism require sophisticated production

<sup>3</sup> In another study, the cost of the tower was estimated at \$1.50/kg (Malcolm and Hansen 2002).

techniques, hence are relatively more expensive (Blanco, 2009). Standard components are used in other industrial sectors and are more established on the market. Moreover, components are categorised according to the loading on the component. Heavily loaded components designed to withstand large amounts of stress are relatively more expensive. Components within a category are also further categorised according to the manufacturing techniques of the major raw materials.

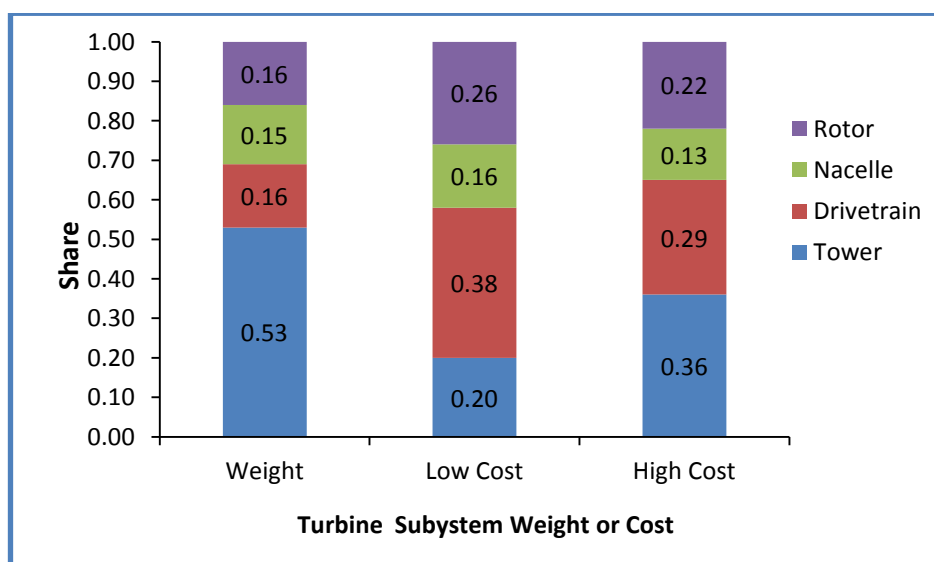
### 6.3.2 Turbine Cost Results

The result of the costs for the components and major subsystems estimated from the components weights from Table 5.16 and specific costs and are given in a range with a low value and high value derived from Table 6.2. The results are shown in Table 6.3.

| <b>Component</b>                | <b>Weight<br/>(tonnes)</b> | <b>Low Cost<br/>(€1000)</b> | <b>High Cost<br/>(€1000)</b> |
|---------------------------------|----------------------------|-----------------------------|------------------------------|
| 3 Blades                        | 20.1                       | 203                         | 254                          |
| Hub                             | 15.8                       | 103                         | 142                          |
| Pitch Mechanism                 | 3.2                        | 60                          | 80                           |
| <b>Rotor</b>                    | <b>39.1</b>                | <b>366</b>                  | <b>476</b>                   |
| Bedplate                        | 26.1                       | 104                         | 164                          |
| Nacelle covering                | 7.4                        | 28                          | 47                           |
| Yaw Mechanism                   | 4.2                        | 43                          | 53                           |
| <b>Nacelle subsystem</b>        | <b>37.6</b>                | <b>175</b>                  | <b>264</b>                   |
| Shaft                           | 4.4                        | 45                          | 55                           |
| Bearings                        | 1.1                        | 11                          | 14                           |
| Gear Box                        | 15.7                       | 159                         | 198                          |
| Mech Equipment                  | 3.12                       | 30                          | 38                           |
| Generator (DFIG)                | 5.5                        | 66                          | 83                           |
| Power Converter                 | 1.0                        | 18                          | 23                           |
| Electric Equipment              | 7.7                        | 52                          | 65                           |
| <b>Drivetrain</b>               | <b>38.5</b>                | <b>436</b>                  | <b>516</b>                   |
| <b>Drivetrain &amp; Nacelle</b> | <b>76.2</b>                | <b>610</b>                  | <b>780</b>                   |
| <b>Tower 85 m</b>               | <b>153.0</b>               | <b>229</b>                  | <b>383</b>                   |
| <b>Turbine (85 m)</b>           | <b>268.0</b>               | <b>1 207</b>                | <b>1 639</b>                 |
| <b>Turbine (60 m)</b>           | <b>243.0</b>               | <b>1 138</b>                | <b>1 740</b>                 |

**Table 6.3 Turbine Cost Results based on Table 5.16 and Table 6.2**

Figure 6.3 shows the distribution of weight and the costs between the major subsystems.



**Figure 6.3 Shares of Weight and cost shares of wind turbine subsystems**

Although the tower has the most significant share of turbine weight, estimated at 53% of the total weight, its low cost at 20% of the total turbine cost is relatively lower than that of the rotor and the drivetrain. This is because the tower material is relatively cheap and the tower tubular structure is not complex to manufacture. At 20%, the cost is however still significant due to the heavy weight. In some turbine designs the tower cost can be as high as 30% of the turbine costs. (Milborrow, 2012).

The other 3 subsystems have nearly equally distributed weight with the heaviest components being in each of the subsystems: blades in the rotor, gearbox in the drivetrain and the bedplate or mainframe in the nacelle. The costs however, differ for the subsystems. The drivetrain is the most complex subsystem of the turbine comprising electronics, electrical, mechanical, electrical and structural elements and is therefore the most expensive subsystem. The rotor is the most specialised part for wind and is hence typically more expensive than the nacelle and the tower.

## 6.4 Balance of Station

### 6.4.1 General

Balance of station (BOS) costs or installation costs are all the costs necessary for the manufactured turbine to be installed at the site. The main constituents are: transport of the turbine components and subsystems from the supplier to the installation site;

necessary roadworks as well as other construction at the site; assembly at the site; foundation for the turbine; and grid connection costs. The majority of installation costs are site specific and are dependent on the size of the wind energy project. The BOS costs estimated for this study are calculated based on a single 2 MW reference turbine, taking into consideration that in reality MW turbines connected to the grid are installed in a windfarm with a number of turbines installed together. It is obviously cheaper to connect many turbines in the same location, rather than just one.

All the engineering assessment models used to estimate BOS in this study are derived from those previously used by NREL using relevant factors to account for inflation and currency conversion from \$s to €s as well as adjustments necessary for the current work (Fingersh, 2006)<sup>4</sup>. The costs are modelled mainly based on the rated power ( $P$ ) as well as the turbine diameter ( $D$ ) and the Height ( $H$ ).

#### **6.4.2 Site Assembly Costs**

Turbine components are transported from the manufacturer either as individual components to be assembled at the site or as subassemblies, preassembled at the manufacturer's company as transportation allows. Typically, the tower is erected first using large cranes by placing tower sections on top of each other and securing them using bolts (Gamesa, 2009). The nacelle frame, gearbox, generator, electrical connections and finally cladding can be assembled at the manufacturing plant and transported to the windfarm as a unit. On the site any remaining nacelle mechanical and electrical equipment and connections are installed in the nacelle subassembly on the ground before it is taken up and put in place on top of the tower. The rotor installation follows with the blades either connected to the hub and the cone on the ground and the rotor assembly is taken up the tower or the hub is taken up and connected to the nacelle and the blades are then taken up one by one. At each stage testing is done to ensure the safety and functionality of each component. The rear part of the bedplate serves as a foundation for controller panels, cooling system and

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<sup>4</sup> NREL studies estimate costs in US\$ whereas this study estimates costs in Euros (€). A currency conversion factor of \$1to €0.8 is used as an average for 2005 figures and an index of 1.130 is used to account for inflation as discussed earlier and given in Table 6.1.



transformer (EWEA, 2012). The electrical connections are assembled in the controller panels (Gamesa, 2009). To estimate assembly costs the following relationship is used:

$$\text{Assembly and installation costs} = 2.22 \times (H \times D)^{1.1736} \quad 6.3$$

Where diameter,  $D = 80$  m and height,  $H = 85$  m for the 2 MW reference turbine.

### 6.4.3 Civil and Roadworks Costs

These include costs for road modification and disruptions to allow for the transportation of the enormous turbine components. The costs are more site specific than assembly costs and are highly dependent on the local authority where the windfarm is located. A cost factor per kW for the civil and roadworks can be estimated as:

$$\text{Civil works cost factor} = 0.9(2.17 \times 10^{-6}P^2 - 0.015P + 69.54) \quad 6.4$$

### 6.4.4 Transportation Costs

Transport costs are dependent on the distance between the manufacturer and the windfarm. Special kind of transportation is required to transport massive components and subsystems. Figure 6.4 shows a single blade being transported to a wind site to illustrate the size of MW wind turbine components.



**Figure 6.4 Wind turbine components transportation**  
[\(<http://www.windenergyplanning.com>\)](http://www.windenergyplanning.com)

If the turbine or some of its components are imported from another country then this cost will include shipping costs and other import costs. Some companies are now setting up plants in customer countries to avoid transportation cost. Due to the size and weight of wind turbine components, transportation can be expensive. For example; the cost to ship 120, 2 MW Acciona wind turbines from Spain to the port in Duluth, Minnesota America in 2007 was \$13.7 million (€10 million), an average cost of over \$110,000 per turbine (Rogowsky and Laney-Cummings, 2009). It is assumed for this study that the turbine components will be manufactured locally in the UK or within Europe so as to keep the costs low. The cost to bring the turbine components and subassemblies is modelled as a function of machine rating and the cost factor is given by:

$$\text{Transport cost factor} = 0.9(1.58 \times 10^{-5}P^2 - 0.0375P + 54.7) \quad 6.5$$

#### **6.4.5 Foundation Costs**

Foundations for onshore turbines are normally made of reinforced concrete. Figure 6.5 shows a typical 2 MW Turbine foundation



**Figure 6.5** Foundation of a Vestas V80 2 MW turbine at Glenkerie windfarm  
<http://premierconstructionnews.com/>. Accessed on 11 June 2012

The foundation cost is a function of the hub height,  $H$  and swept area,  $A_{swept}$ .

$$\text{Foundation costs} = 273(A_{swept} \times H)^{0.4037} \quad 6.6$$

#### 6.4.6 Grid-connection Costs

The more turbines installed together, the cheaper the installation cost per turbine. On the other hand, there are limits to the amount of electrical energy local electrical grids can handle. If the local grid is too weak to handle the output from the turbine, there may be need for grid reinforcement. The responsibility for grid reinforcement whether it is the power company or the owner of the windfarm or other authority varies from country to country. Grid connection costs are dependent on the rated power ( $P$ ) and the cost factor per MW of rated power can be estimated from:

$$\text{Grid cost factor} = 0.9(3.49 \times 10^{-6}P^2 - 0.0221P + 109.7) \quad 6.7$$

#### 6.4.7 Engineering and permits

Engineering and permits cover the cost share for each turbine of all design work necessary at the site and are dependent on the location, environmental conditions and local permitting requirements.

$$\text{Engineering cost factor} = 0.9(9.94 \times 10^{-4}P + 20.31) \quad 6.8$$

Table 6.4 presents the results for the Balance of station (BOS) costs estimated from the models described in this section for the 2 MW reference turbine at tower height ( $H$ ) of 85 m. The higher values for the BOS components are assumed to be 10% higher than the low range values.

| <b>BOS component</b> | <b>Design Driver/ Cost Function (€/kW)</b> | <b>Cost (€1 000) Low level</b> | <b>Cost (€1 000) High level</b> |
|----------------------|--|--------------------------------|---------------------------------|
| Foundations          | $H$ and $D$                                | 58                             | 64                              |
| Transportation       | 38.65                                      | 76                             | 84                              |
| Civil and Roadworks  | 44.30                                      | 91                             | 101                             |
| Assembly             | $H$ and $D$                                | 55                             | 61                              |
| Grid & Connections   | 71.51                                      | 141                            | 156                             |
| Permits              | 20.07                                      | 40                             | 44                              |
| <b>BOS Total</b>     | <b>~231.00</b>                             | <b>462</b>                     | <b>508</b>                      |

**Table 6.4 Balance of station (BOS) cost results**

The grid connection costs are the highest for this cost centre and as mentioned earlier, these vary from country to country depending on the existing grid and the energy policies in the country. In most cases, the grid networks were built and designed for the electricity from the ideally located conventional source power plant whereas, the location of windfarms is mainly determined by the wind resources. This necessitates a great need to strengthen grid networks to accommodate electricity from the intermittent wind energy.

## 6.5 Installed Capital Costs (ICC)

The summation of the turbine costs from Table 6.3 and the BOS costs from Table 6.4 give the ICC which represents the level of investment required at the start of the project.

The turbine costs which were estimated are costs to the turbine manufacturer who supplies to the turbine developer. The cost of the turbine to the developer includes a profit margin or mark up as a percentage of the net cost. For this study, a typical profit margin of 15% is used, based on the fact that Vestas reported a gross profit of 15.3% for the company in the first quarter of 2012 (Vestas, 2012c).

The detailed assessment for the 2 MW reference turbine was not based on an actual existing project and is therefore associated with a degree of uncertainty. Variations in project specific factors and market factors on the ICC components increase the degree of uncertainties in the results. In a wind energy cost review for the US government by the National Renewable Energy Laboratory (NREL), a market adjustment factor around 22% of the ICC was used to adjust for the difference between modelled costs and market price of a typical wind turbine.

In addition to the profit margin already addressed for the Vestas 2 MW reference turbine cost, a factor of 10% of the ICC is used to account for project uncertainties. Table 6.5 gives the summary of the investment costs for both the low level and the high level giving the result in a range. It also includes the normalised ICC per MW.

| <b>ICC components</b>                                 | <b>Cost (€1 000)<br/>Low level</b> | <b>Cost (€1 000)<br/>High level</b> |
|---|------------------------------------|-------------------------------------|
| Turbine Net Cost (A)                                  | 1 206                              | 1 639                               |
| Cost to developer (1.15A)                             | 1 387                              | 1 884                               |
| Turbine Cost/MW $\left(\frac{1.15A}{P}\right)$        | 693                                | 942                                 |
| BOS Total (B)   | 462                                | 508                                 |
| ICC (C = A + B)                                       | 1 849                              | 2 392                               |
| Project Uncertainty (0.1C)                            | 185                                | 239                                 |
| Total project ICC (1.1C)                              | 2 034                              | 2 632                               |
| Normalised ICC Cost/MW $\left(\frac{1.15C}{P}\right)$ | 1 017                              | 1 316                               |

**Table 6.5 Installed Capital Costs (ICC) estimations for the 2 MW Reference from Table 6.3 and Table 6.4**

To allow comparisons with other turbines or projects, the ICC is normalised per unit installed capacity either per kW or MW. The estimated BOS costs make up around 25% and the turbine 75% of the ICC excluding project uncertainty costs, a share typical for wind energy projects. (Tegen, Hand et al., 2012).

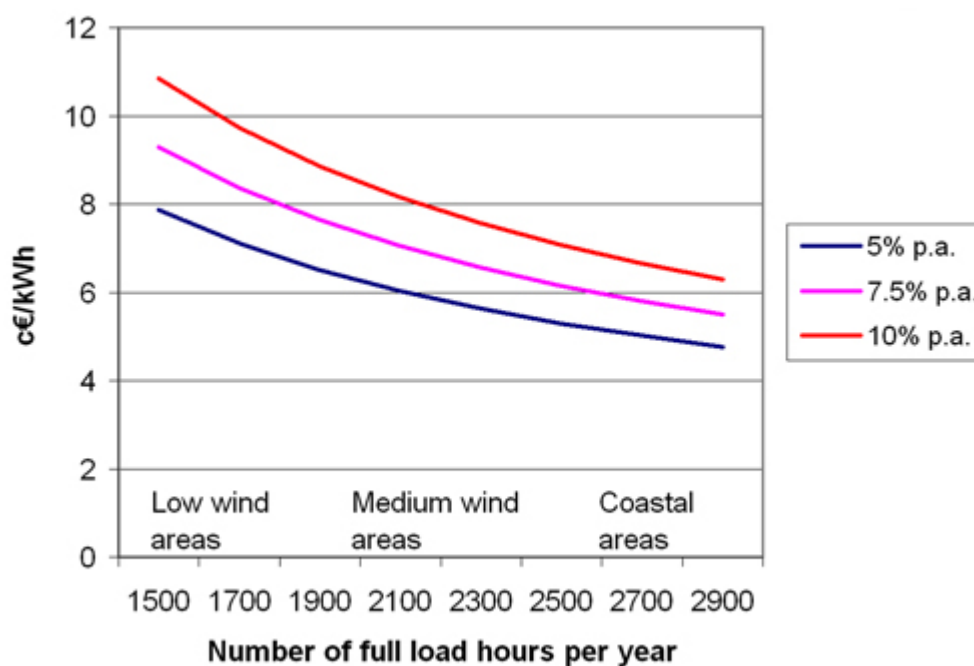
## 6.6 Operation and Maintenance (O&M) Costs

The annual O&M costs make a significant contribution to the COE. These include scheduled and unscheduled turbine maintenance; parts and supplies for equipment and facilities maintenance; administrative and support labour costs. Another component is the land lease costs for rental or lease fees charged for installed turbines. The costs may also include levelised replacement costs for major replacements (Blanco, 2009). O&M costs can be lower in the first few years when the turbine is covered by warranty. Very few operational, if any, modern turbines in the MW range have been installed long enough to understand their operation over a 20 year lifetime. For example, Gamesa installed its first 2 MW wind turbine in 2002 (Gamesa, 2012; WEM, 2012).

Turbine O&M costs can either be expressed as a fixed cost in terms of €/annum or they can be a variable expressed as €/MWh, of which the latter is commonly used. According to EWEA, all O&M costs for onshore wind energy are generally estimated to be in the range 12 to 15 €/MWh of wind produced over the total lifetime of a turbine which for most projects corresponds to 10 to 20% of the total costs (Blanco, 2009; Morthorst, Auer et al., 2009; EWEA, 2012). Following the EWEA estimates, an average low value of 13.5 €/MWh and high value of 15 €/MWh are used for this study.

## 6.7 Project Finance Costs

The cost of financing the project or the cost of capital of the lifetime of the project is taken into account in the COE calculation by the use of the discount rate. An economic analysis for onshore wind energy carried out for the EWEA assumed the discount rate ranged within an interval of 5% to 10% a year and in the calculations a value of 7.5% was used (Morthorst, Auer et al., 2009). Figure 6.6 shows results of their analysis on the impact of the discount rate on COE for different wind regimes shown in terms of full load hours of operation. The impact of the discount rate is more pronounced in lower wind areas because of the increased risk in the performance.



**Figure 6.6** COE and Discount Rate (Morthorst, Auer et al., 2009)

In this thesis a discount rate of 7.5% is used as in the EWEA studies for the low range and 8.5% for the high range.

## 6.8 Annual Energy Production

The performance of the turbine expressed as the yield in kWh or MWh of electricity generated by the turbine annually is the prime value and purpose of the wind turbine system. Any increase in the energy yield has a direct effect of reducing COE (Jamieson, 2011). As mentioned in Chapter 4, the performance of a turbine is dependent on the way it interacts with the wind regime, and this requires a proper match of the turbine characteristics and the wind regime in which it works. Although a turbine's performance is highly dependent on the site characteristics, it is not economical to design models specific for particular sites, as different sites have different wind regimes. Instead, manufacturers develop modular turbine designs for different classes of wind regimes. For example, for low wind sites, a developer would choose the 2 MW Vestas turbine with a high hub height.

To accomplish the aims of this work it was important to specify a representative site where the turbine would be installed. A hypothetical site was chosen near

Dunstaffnage in Scotland. This was chosen because wind data was available for that area (DAWI, 2012).

Yield is estimated by analysis of:

- Wind turbine characteristics (capabilities) represented by power curves provided by the manufacturer (Akdağ and Güler, 2010; Vestas, 2012).
- The site's wind resource data and the wind speed probability estimated using the Weibull distribution (Bhattacharya, 2011).
- The turbine's availability and reliability (Tavner, Xiang et al., 2007).

The turbine efficiency or particularly, the drivetrain efficiency is another important parameter in estimating the performance of the turbine. This is considered separate and not included in the AEP estimation and will be discussed in Section 6.8.5.

### **6.8.1 Capacity Factor**

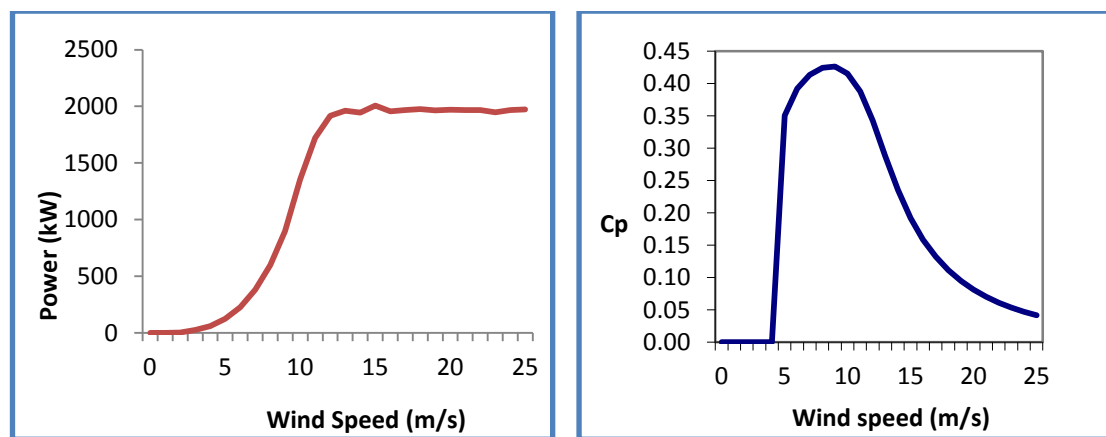
Given the rated power of a wind turbine generation system, the capacity factor is a good indicator that best characterises the electricity generating capacity of a wind farm and can be derived from the power curve. It expresses the percentage of time that a wind farm is producing electricity at rated capacity in a year (Blanco, 2009). The capacity factor is influenced by the availability of the turbine to the prevailing wind. Capacity factor does not directly quantify the hours the turbine is operational but when it is operational at rated power. Most turbines generate for a considerable time but not at full rating. Normally capacity factor estimations take into account availability and all the losses as observed for operational turbines (Tavner, Xiang et al., 2007). Average capacity factors for different localities differ because of the differences in wind regime. Typical capacity factors are estimated for countries depending on the wind resource. In Europe, UK with high wind speeds, has one of the highest capacity factors of around 30% for onshore turbines (Sinden, 2007; BWEA, 2012a). This capacity factor is used for rough estimations of the yield for this study.



### 6.8.2 Wind Turbine Characteristics

The operational parameters of the 2 MW reference turbine are based on the Vestas V80 given in Table 5.1. Typically rated wind speed is in the range 11-13 m/s. The Vestas V80 has a high rated wind speed of 15.6 m/s. Though there is more power in high speeds, the rated speed is designed to be much less than the cut-out wind speed of 25 m/s. If a turbine is designed to produce power at 12 m/s it would mean that it would produce power  $(25/12)^3$  times more at 25 m/s. This would drive the cost of the drivetrain very high which is typically 40% of total cost (Jamieson, 2011). In this study the drivetrain cost was estimated to account for 36% of the total turbine cost (see Figure 6.2). The drivetrain efficiency will be lower at part loads. This is in consideration of the infrequency of wind speed above 15 m/s and the probability of the wind blowing at full load at 25 m/s. Therefore the turbine is designed at rated speeds far much less than the cut out speed (Jamieson, 2011).

Manufacturers specify the power curve and capacity factor of the turbine dependent on its design. For absolute values, official power curve documentation from manufacturers is required to fully assess and compare turbine performance for a given wind regime represented in curves (Maples, Hand et al., 2010). Figure 6.7 shows the power curve developed and the power coefficient ( $C_p$ ) curve for the 2 MW reference turbine.



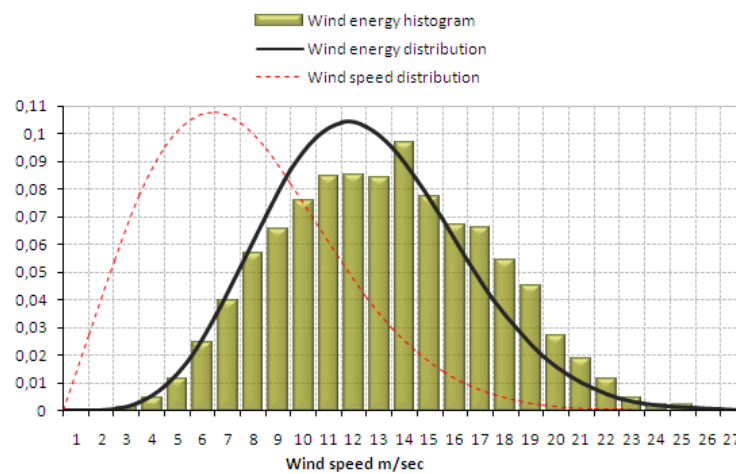
**Figure 6.7** 2 MW power curve and the power coefficient ( $C_p$ ) curve

### 6.8.3 Wind Resource

The Weibull distribution used to estimate wind speed distribution is characterised by two parameters; one is the shape parameter  $k$  (dimensionless) and the other is the scale parameter  $c$  (m/s) (Bhattacharya, 2011). The cumulative distribution function of wind speed  $v$  is given by:

$$f(v) = 1 - \left(e^{-\left(\frac{v}{c}\right)^k}\right)^K \quad 6.9$$

Figure 6.8 shows typical distribution for wind speeds in the operational range.



**Figure 6.8** Weibull distribution (DAWI, 2012)

### Windfarm characteristics

The wind turbine characteristics for the windfarm based in Dunstaffnage were obtained from the Danish Wind Energy Association Wind Turbine Guided Tour Power Calculator which has a database of a number of sites and calculates the power for some common commercial wind turbines. Table 6.6 gives the wind distribution data for the site for the wind turbine characteristics for the V80 2 MW.

| Wind distribution                 |       |
|-----------------------------------|-------|
| Weibull shape parameter k         | 1.93  |
| Wind mean speed, ms <sup>-1</sup> | 7.048 |
| Weibull Scale Parameter           | 7.95  |
| Roughness length                  | 0.055 |
| Wind Class                        | 1.5   |

**Table 6.6      2 MW reference turbine and site parameters at a windfarm in Dunstaffnage (DAWI, 2012)**

#### **6.8.4 Availability and Reliability**

The energy output is dependent on the wind turbine's availability to function as intended throughout its lifetime. Wind turbine availability is the capability to operate when the wind is blowing and the wind turbine is not undergoing maintenance. The reliability and hence the availability of the turbine is related to the components in the system. The reliability and availability of a wind turbine impact directly on energy produced and therefore are of important value when estimating the COE. Elimination of any component without compromising the functionality of the turbine always has added value on COE, beyond the removal of capital costs; associated issues of maintenance and reliability are reduced. (Jamieson, 2011).

Availability is estimated as a percentage is given by:

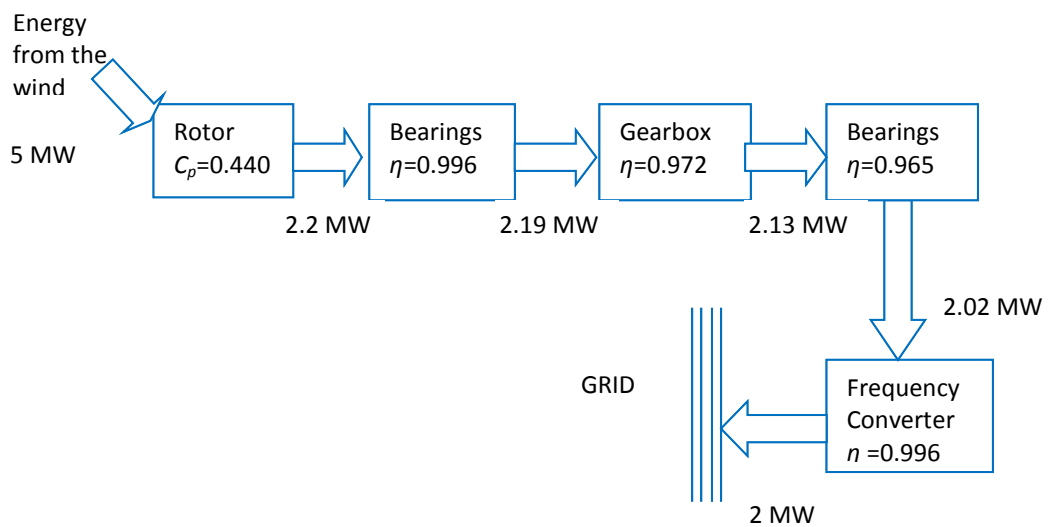
$$A_{wt} = \frac{T_t - T_D}{T_t} \quad 6.10$$

Where  $T_t$  is the total operational time and  $T_D$  is the total down time due to scheduled maintenance, grid downtime and time when wind or other ambient conditions are outside specification. Other down time might include shutdown for other reasons other than unsafe conditions, access limitations and "Act of God" incidents. Manufacturers availability quote is typically 98% or above for modern European machines and operators quote a lower availability of 97% (Tavner, Faulstich et al., 2011). In this study an availability of 98% is used for the 2 MW reference turbine.

### 6.8.5 Turbine System Efficiency

The system efficiency is also extremely important in the estimation of turbine performance, affecting a significant proportion of annual energy output in wind speeds at part loads below rated power (Jamieson, 2011). The major efficiency losses which are shown in Figure 6.9 are due to: the aerodynamic rotor  $C_p$  and drivetrain efficiencies. The rotor  $C_p$  is considered in the estimation of the rated power as mentioned in Chapter 5. The major unavoidable losses that reduce the efficiency along the electro-mechanical drivetrain are as follows:

- i. Frictional losses in bearings and seals of rotor shaft,
- ii. Gearbox losses
- iii. Generator losses
- iv. Electric and inverter losses



**Figure 6.9** Typical efficiencies for different major components for a 2 MW turbine (Hau, 2006)

For the 2 MW reference turbine, the efficiency calculation is not taken into account in the yield estimation, but will be dealt with separately in the COE estimation, as this will help in further post detailed assessment modelling work. The initial total turbine efficiency for the study is derived from Figure 6.9 for the 3 stage gearbox with DFIG generator 2 MW reference turbine is 91%. This value is in line with other studies (Li and Chen, 2008). Further estimation of the system efficiency is performed

in the next chapter where alternative drivetrain and part load efficiencies are considered.

### 6.8.6 Estimated Yield Results

An initial estimation for the 2 MW reference turbine installed in the UK using an average capacity factor of 30% (assuming the availability of 98% is taken into account in the capacity factor estimation and the 91% system efficiency is not taken into account) results in a yield of 5 256 000 kWh (5 256 MWh). If the efficiency is included in the yield estimation a value of 4 782 960 kWh is obtained. A more detailed estimation that takes into account the wind regime was carried out using the model provided by The Danish Wind Energy Association for the site at Dunstaffnage and Table 6.7 gives the results that were obtained.

| Input  |     | Outputs                        |       |
|--|-----|--------------------------------|-------|
| Power input, W/m <sup>2</sup>                | 520 | Power output, W/m <sup>2</sup> | 118   |
| Max power input wind speed, ms <sup>-1</sup> | 15  | Energy, kWh/m <sup>2</sup> /yr | 1 038 |
| Mean hub height wind speed, ms <sup>-1</sup> | 7.5 | Energy output (AEP), MWh/year  | 5 214 |
|  |     | Capacity factor, %             | 30    |

**Table 6.7 Annual energy production (AEP) Estimate Results**

Windstats in Europe based in Denmark collects information of operational turbines in some areas in some European wind farms and publishes data in the Windstats newsletter quarterly. Unfortunately, for the period 2008 to 2009 no data was collected from United Kingdom, only for Finland, Denmark, Germany and Sweden.

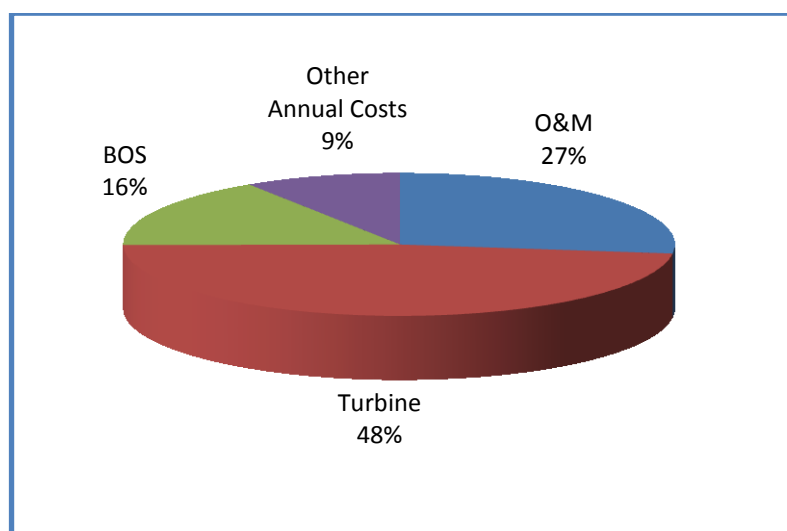
There difference in the values of the annual yield estimates using the capacity factor average 5 256 MWh and that estimated from the Danish Wind Association model, 5 214 MWh, is minimal. In this thesis the value 5 256 MWh is used as the maximum estimated yield for the lower cost range for the 2 MW reference turbine.

## 6.9 COE Estimates Results

| COE Parameter                   | Value- Low | Value- High |
|---------------------------------|------------|-------------|
| ICC, €                          | 2 034 000  | 2 879 000   |
| O&M, € (p/a)                    | 63 072     | 75 986      |
| Total Annual Costs, € ( p/a)    | 95 054     | 123 656     |
| Project Financing (DR), %       | 7.5        | 10          |
| System Efficiency ( $\eta$ ), % | 91         | 90          |
| Yield (AEP), MWh                | 5 256      | 5 066       |
| COE, ¢cents/kWh                 | 5.00       | 7.34        |
| COE, €/MWh                      | 50         | 73          |

**Table 6.8**      **2 MW reference turbine COE results estimated using Equation 6.1**

The estimated COE for a 2 MW turbine installed in the UK is between 50 and 73 €/MWh depending on the project and the installation site. Figure 6.10 shows the shares of the major cost centres for the COE.



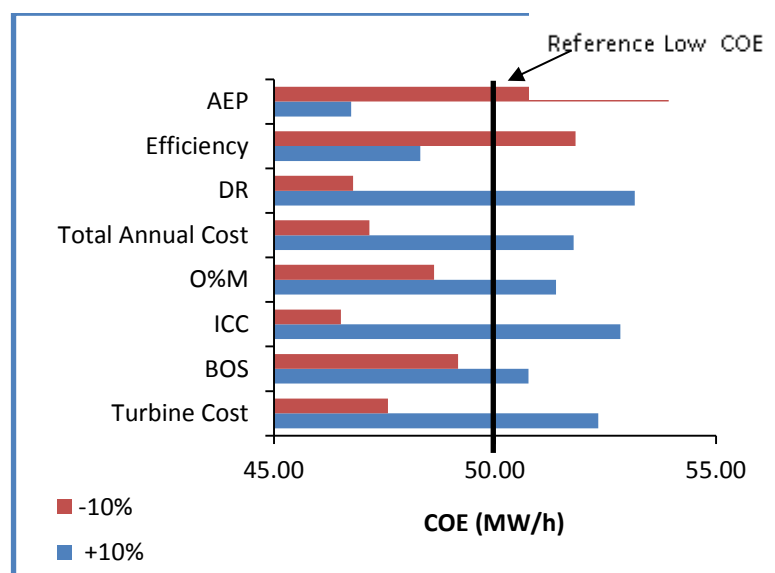
**Figure 6.10**      **COE Components shares (%)**

The ICC (Turbine + BOS costs) which account for 64% of the COE is the highest cost centre with the turbine constituting 75% of the ICC.

Hence innovation and technological improvements of the turbine and its components play an important role in wind energy technology cost reductions.

### 6.9.1 Sensitivity Analysis

For generic modelling it is important to consider the impact of errors in the main parameters of the estimation. The relative magnitude of errors can be assessed by doing a sensitivity analysis to gauge which component of the COE has the greatest impact if its value is overestimated or underestimated by a certain percentage, say 10%. Figure 6.11 shows the sensitivity analysis carried out to find the impact on COE of changing the major parameters that constitute the COE calculation. The parameters were each increased by 10% holding all the other parameters constant except for the system efficiency which was increased from 91% to 96% and decreased to 86%. The values used for the parameters are those on the lower end of the range estimated above. The modelled COE is approximately 50 €/MWh for the 2 MW turbine.



**Figure 6.11 COE Sensitivity Analysis**

Increasing the yield (AEP) by 10% has a positive impact of reducing the COE by 6.5%. The 10% increase in yield is the same as 10% increase in the capacity factor from 30% to 33%. An increase in system efficiency reduces the COE but has a significant direct effect on power and energy capture only in wind speeds below rated.

Figure 6.11 also shows that 10% increase in the discount rate has the greatest negative impact of increasing the COE by 6.3% to 53.16 €/MWh followed by the ICC which results in a 5.7% increase of the COE to 52.84 €/MWh. The impact of change of the discount rate is not addressed in detail in this study as it is highly project specific dependent on a number of financial factors such as whether the project is publicly or privately funded and the risk associated with the project. Of the two, the ICC is the one that can be influenced by technological innovations and learning effects. Research tends to focus on the capital cost of wind energy, which was estimated at 75% for the 2 MW reference turbine and can be as high as 80% of the project costs (Blanco, 2009; Schwabe, Lensink et al., 2011).

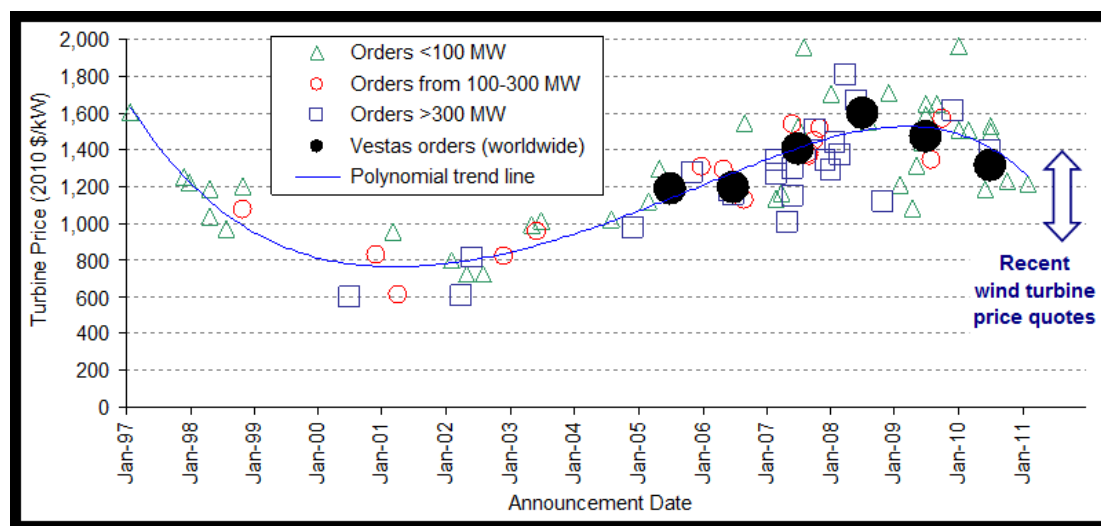
## 6.10 Discussion

Cost of energy (COE) is the most relevant analysis metric for the assessment of emerging energy technologies as it takes into account of all constituent cost centres into its calculation allowing detailed analysis of cost reduction potential. COE is highly dependent on the wind regime making cost estimation very project specific thereby posing challenges for generic modelling. However, since wind turbine technology is now well established, reasonable assumptions can be made for the 2 MW reference turbine and for a representative site. COE has the advantage of allowing comparison between different technologies. On the other hand, the Installed Capital Cost (ICC) can be estimated in general without any specific site considerations.

As illustrated by the modelled ICC results, wind energy is capital intensive compared to other conventional fossil fuelled technologies where up to 40 to 50% are related to fuel and O&M costs (EWEA, 2012). Alternatively, modelling capital costs (ICC) can significantly represent wind energy costs in place of COE. This can be a strategic approach for studies that analyse the relative impact of change as is the case with this study if there are data and methodological limitations. In some cases the turbine costs or turbine price trends can be used to make an economic analysis of wind energy technology.



Figure 6.12 shows the prices of Vestas turbines and other commercial turbines in the United States, but estimated in \$/MWh. Information as to the technological development of wind energy can be derived from such data. Though the chart was constructed using turbine price data, this has a reflection on the turbine cost and consequently on the COE.



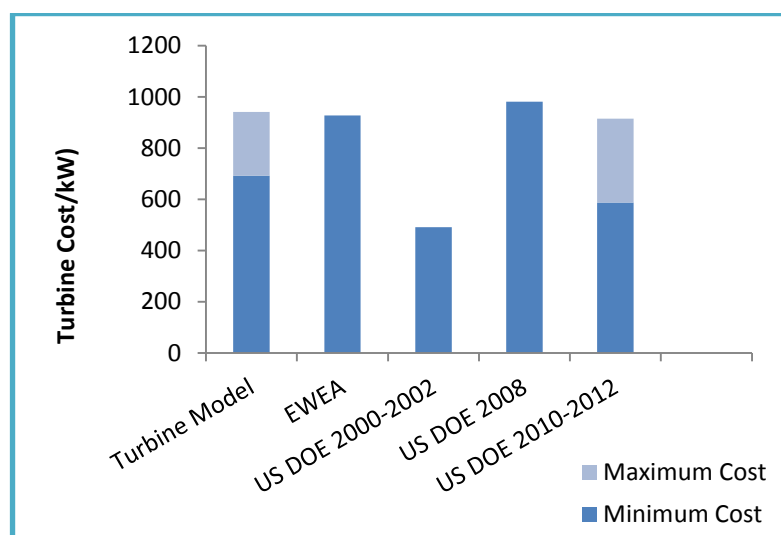
**Figure 6.12 Wind turbine prices in the United States (Lantz, Wiser et al., 2012).**

The resulting cost range estimated in this study of between 50 €/MWh and 73 €/MWh is not far from estimates in earlier European studies (Morthost and Jacobsen, 2003). In 2009, Morthost et al., for the European Wind Energy Association (EWEA), projected the production costs for a 2 MW wind turbine installed in an area with a medium wind onshore around 61 €/MWh (Morthorst, Auer et al., 2009). Assuming that the total capacity doubled in three years, it was projected that in 2015 the cost range would be approximately 43 to 50 €/MWh for a coastal and inland site respectively. It was also predicted that if the capacity doubled in five years this would imply a cost range in 2015 of 48 to 55 €/MWh.

The projections in 2009 were highly dependent on the wind regime and were based mainly on countries such as Denmark, a fairly cheap wind power country, whereas for more expensive countries the cost of wind power produced would increase by 10-20 €/MWh (Morthorst, Auer et al., 2009). Earlier in 2008, Blanco had presented outcomes of a study on the generation costs of wind energy projects carried out

among wind energy manufacturers and developers. The results gave a range of COE of between 45 and 87 €/MWh for onshore wind and 60-111 €/MWh for offshore. It was observed that there was an increase of about 20% from around 2005 to 2008 due to increases in strategic raw materials at a time when global demand increased as discussed in Chapter 3 and Chapter 4 (Blanco, 2009). A review for the US government by the National Renewable Energy Laboratory (NREL) estimated levelised COE in the range 58-108 \$/MWh based on modelled and market based data for onshore wind energy. A project based estimate based on a 1.5 MW turbine was placed at 71 \$/MWh (Tegen, Hand et al., 2012). A more recent update of the review indicated a wider range of 50-148 \$/MWh (Tegen, Lantz et al., 2013).

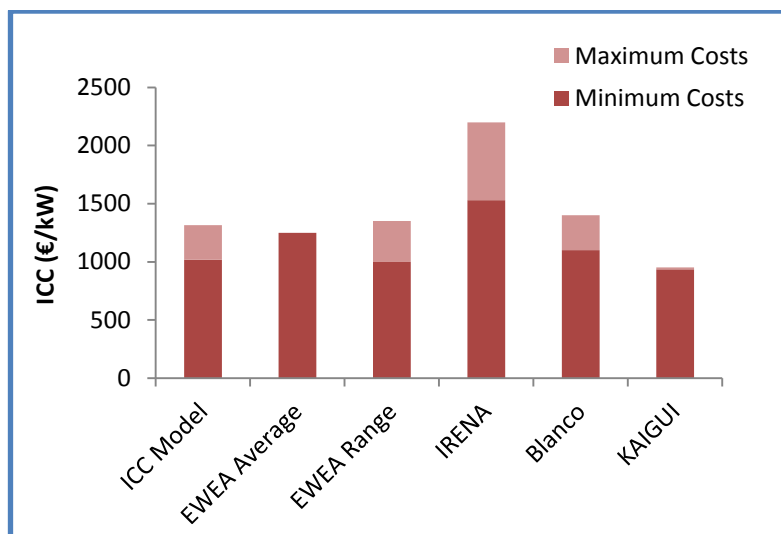
Figures 6.13 compares modelled turbine costs with those from other studies and reports.



**Figure 6.13 Turbine Costs (Morthorst, Auer et al., 2009; Wiser and Bolinger, 2011)**

The first column represents the modelled turbine costs for this study in the range 693 to 942 €/kW. The EWEA estimate for the turbine cost was based on a typical 2 MW turbine installed in Europe in 2006. The US DOE market reports were based on a study that looked at drivers that caused cost increases in the 2000s and were based on price data for 81 turbines installed in the US between 1997 and 2011 (Bolinger and Wiser, 2011; Wiser and Bolinger, 2011; Wiser and Bolinger, 2012). Figure 6.14

compares ICC costs with other costs from publicly available sources. The modelled ICC costs for the 2 MW reference turbine are shown in the first column.



**Figure 6.14 ICC Costs (Blanco, 2009; Morthorst, Auer et al., 2009; Kaigui and Billinton, 2011; EWEA, 2012; IRENA, 2012)**

The wide range of ICC market data values reflects the uncertainties associated in modelling absolute values for the COE. However project based reference cases can be used to observe the trends in the technology and quantify the impact of change to any of the COE components.

## 6.11 Conclusion

In this chapter the cost of energy (COE) of the 2 MW reference turbine was estimated from its cost constituents. The costs were estimated in a range giving a lower and an upper cost value. The costs of the wind turbine components were estimated using the weight results from the Sunderland based models given in Chapter 5 and derived specific costs in €/kg or in €/MW of rated power for some electrical components. The balance of station (BOS) costs were then estimated and added to the turbine costs to give the total installed capital costs (ICC) per installed capacity. The cost of energy (COE) in €/kWh was then calculated from the estimated ICC, the annual operation and maintenance (O&M) costs, the annual energy production (AEP) and the project financing represented by the discount rate (DR). A

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hypothetical site was chosen in Dunstaffnage, Scotland as the windfarm location for the analysis.

The cost results of the engineering assessment, though they agree considerably with other documented results, they cannot be treated solely on their own with great confidence as absolute COE values. This is mainly because they are not based on a specific wind energy project. Although the 2 MW reference turbine was based on the commercial Vestas V80 turbine, not all the data came from the manufacturer. With improved data availability for inputs and validation, the methods can give absolute results with higher levels of credibility. However, the results given in this chapter suffice for the purpose of this study serving as important inputs for further analysis that allows the assessment of the relative impact of change to the turbine on wind energy costs. The use of parametric modelling to modify the weight and cost results obtained through the engineering assessment methods outlined in Chapter 5 and 6 so as to allow the quantification of technological changes to the wind turbine is addressed in the next chapter.

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## 7 Parametric Modelling

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### 7.1 Introduction

Over the years, technological improvements and innovations have been pivotal in bringing the cost and the price of wind energy within reach of conventional fossil-fuel electricity. The future of wind energy is highly dependent on continued efforts to reduce costs in the future. As was discussed in Chapter 4, the turbine design has gradually evolved. The major change has been the gradual upscaling to MW turbines on the market, conceptual radical changes to some components especially in the drivetrain and the move to offshore developments. This chapter focused on the use of parametric models to modify the weight and cost of the 2 MW reference turbine so as to assess the impact of wind turbine upscaling and the radical drivetrain changes.

The benefits of innovation are realised if it is properly managed and its impact is understood, otherwise it becomes costly. The assessment of change is necessary for the yet costly emerging technologies requiring improvements to increase competitiveness. It is necessary to investigate if the impact of technical change on cost is significant enough to be taken into account in models that analyse and forecast cost trends. The methods developed and used for the detailed engineering assessment sufficed for the 2 MW reference turbine. However, when a number of alternatives are to be considered, the detailed analysis can be resource consuming and lesser detailed methods are hence required.

Parametric modelling was chosen to analyse the impact of innovation of wind turbines on the cost of the turbines, the installed capital cost (ICC) and the cost of energy (COE). On their own, the absolute cost results from the engineering assessments for the 2 MW reference turbine have uncertainties associated with component market factors and project specific factors. Parametric modelling potentially makes better use of the results of the engineering assessments by providing means for a relative cost analysis for assessing impact of change. In this

chapter parametric modelling of the 2 MW reference turbine is presented for analysing the impact of gradual upscaling and radical or near radical changes in the drivetrain.

## **7.2 Wind Turbines Innovation**

As wind energy has become established on the market, the design process of the wind turbine has shortened. New turbines enter the market with very short development and testing phases. A number of studies have continued to look at areas that need to be addressed to assure the future of wind energy based on continued cost reduction and competitiveness (Jamieson, 2011; Wiser and Bolinger, 2011; EWEA, 2012; Lantz, Wiser et al., 2012).

The exploitation of possible technological improvements that result in lower capital costs and increased performance is key to reduction of COE. Globally, research areas and innovation technology pathways have highlighted potential for continuous improvement of the wind energy conversion system in areas such as wind resource harnessing; wind turbine components; operation and maintenance (O&M) and turbine reliability and efficiency (Valpy, 2013). At the wind turbine manufacturer level, innovation in concepts at smaller scale specific to the company has been continually introduced to improve competitiveness of turbines as more companies enter the wind industry. Company specific technological developments are not addressed in this study, but rather the focus of this study is on developments typical across the industry globally.

Given that wind energy technology has evolved continually with instances of radical development in some of the components it becomes important to analyse the impact of technological development and the introduction of alternatives to the defined 2 MW reference turbine. It should be noted the alternative concept does not completely replace the old concept rather but its market share increases gradually over time from introduction until it takes over and becomes the major concept. In some cases all the concepts remain on the market with either constant or varying market shares.

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Change in the turbine components mean either:

1. Improvement of existing (e.g. upscaling of the same turbine design)
2. Elimination (e.g. gearless drivetrain)
3. Replacement (e.g. stall to pitch power regulation)

Components in a wind turbine system interact in such a way that a change in one component, whether elimination or improvement, has an impact on other components. The effect on the other components can be minimal to insignificant or can be significant requiring analysis or quantification. Understanding the interaction of components or the dynamics of the interaction is necessary when assessing and quantifying the impact of change. For example, the upscaling to MW has necessitated the need for design improvements or alternative concepts for the larger components and more so for compatibility with grid which has stringent connection and control requirements (Hansen, Cutululis et al., 2009; UPWIND, 2011). Table 7.1 gives a summary of major research and technological development areas discussed in Chapter 4 and the assumed need for modelling to assess their impact on wind technological development for this study.

| Research area    | Innovation Assessment  | References   |
|------------------|--|--|
| Variable Speed   | Not assessed as majority of MW turbines are now variable speed             | (Carlin, Laxson et al., 2001; Li and Chen, 2008; Masmoudi, Abdelkafi et al., 2011)   |
| Pitch regulation | Not assessed pitch and stall costs nearly similar                          | (Polinder, Bang et al., 2007)  |
| Rotor Designs    | Any innovation assumed not significant for current analysis <sup>5</sup> . | (Griffin, 2001; Malcolm and Hansen, 2002; Rivkin, Toomey et al., 2012)   |
| Tower Designs    | Any innovation assumed not significant for current analysis                | (Malcolm, 2004; Gardner, Garrad et al., 2009)  |
| Drivetrain       | Radical development of the subsystem modelled                              | (Bywaters, John et al., 2005; Polinder, Van Der Pijl et al., 2006; Polinder, Bang et al., 2007; Bang, Polinder et al., 2008) |
| Upscaling        | Incremental development modelled   | (Coulomb and Neuhoff, 2006; Fingersh, 2006; UPWIND, 2012)  |
| Offshore         | Modelling of offshore developments will be discussed.                      | (Junginger, Faaij et al., 2004; Greenacre, Gross et al., 2010)   |

**Table 7.1 Major wind turbine technological development areas**

Initially, parametric modelling methods will be used to analyse the impact of incremental upscaling of wind turbines and thereafter, for the direct drive alternative drivetrain as an example of radical development.

### 7.3 Proposed Upscaling Parametric Model

Parametric modelling is based on the establishment of simple mathematical cost estimation relationships (CER) for a component or the turbine. The CERs used to extrapolate costs from the 2 MW reference turbine for this study were developed based on the model Coulomb and Neuhoff used to assess the impact of changing

<sup>5</sup> Although the rotor innovation has been assumed not significant in general, the move to new lighter materials such as carbon fibre blades has an impact on the rotor weight but the impact is counteracted by the cost of carbon fibre materials. Further research is required to explore the use of lighter blade materials whose use become mandatory for larger MW turbines presumably for technical weight reasons.



product attributes of wind turbine (Coulomb and Neuhoﬀ, 2006). The NREL scaling model is also used to check the validity of the resulting model (Fingersh, 2006).

The turbine cost at diameter  $D$ ,  $C_{(D)}$  can be estimated using the following CER:

$$C_{(D)} = C_{ref} \times PF \quad 7.1$$

Where  $C_{ref}$  is the 2 MW reference turbine cost and PF is the parametric factor. From equation 7.1, the parametric factor is then defined as the factor by which the reference turbine cost is multiplied to give the new cost at a new diameter  $D$ . Similar to detailed modelling, weight assessment will also be used to derive CERs for parametric modelling. A simple upscaling model is developed for turbines based on the relationship between the weight ( $W$ ) and independent variable turbine diameter  $D$ . As weight is linear with the cost, the CERs can also be derived from the relationships used for weight. The weight of the turbine at diameter  $D$  can be estimated using the following simple relationship:

$$W_{(D)} = W_{ref} \left( \frac{D}{D_{ref}} \right)^a \quad 7.2$$

Where  $W_{ref}$  is the reference turbine weight and  $a$  is the scaling exponent that represents the power with which the turbine weight scales with the diameter. The scaling is dependent on the turbine components and their cost drivers such as loading and materials.

The cost of the turbine or its components typically has a proportion that is fixed and does not vary directly with weight. If  $\mu$  is defined as the proportion of cost that varies with weight, and  $1-\mu$  is the proportion of the turbine that is fixed, the cost at diameter  $D$  is estimated as:

$$C_{(D)} = C_{ref} \left( \mu \frac{W_{(D)}}{W_{ref}} + (1 - \mu) \right) \quad 7.3$$

To simplify the equations we define the ratio  $D/D_{ref} = r$  (not to be confused with  $R$  the turbine radius). The weight function in Equation 7.1 becomes:

$$W_{(D)} = W_{ref} r^a \quad 7.4$$

Substituting Equation 7.4 into Equation 7.3, the CER becomes:

$$C_{(D)} = C_{ref} (\mu r^a + (1 - \mu)) \quad 7.5$$

Theoretically, it is suggested that the turbine weight scales with  $D$  with an exponent  $a = 3$  but in reality this is different. The turbine is made up of different components with different cost drivers as described in Chapter 5, thus scaling differently with  $D$  as the turbine size increases or decreases. Coulomb and Neuhoﬀ (2006) proposed that components scale with exponents 1, 2 or 3, based on theory:

1. Cubic ( $a=3$ )- for those components whose major design driver is weight such as that of the rotor and stress bearing components
2. Square ( $a=2$ ) - for all components whose weight scales as the rated power such as the electrical generator
3. Linear ( $a=1$ ) - for components whose weight scales directly with  $D$

Generally, the cost of the turbine is estimated from the following CER:

$$C_{(D)} = C_{ref} (\mu x_3 r^3 + \mu x_2 r^2 + \mu x_1 r + (1 - \mu)) \quad 7.6$$

Where  $x_1$  is the proportion of mass that scales linearly with  $D$  with an exponent of 1 ( $a=1$ ),  $x_2$  proportion that scales with 2 and  $x_3$  proportion that scales with 3. To estimate the change in the ICC (installed capital costs) and COE, the CER is normalised with the rated power which in theory scales by the power of 2 with respect to  $D$ . As the turbine size increases, the hub height increases lifting the turbine to faster winds. To take into account of the increased energy capture at higher hub heights, the wind shear ( $\alpha$ ) is used to express the increase in velocity in terms of the height  $H$ . The CER becomes:

$$C_{(D)} = C_{ref} \frac{(\mu x_3 r^3 + \mu x_2 r^2 + \mu x_1 r + (1 - \mu))}{r^2 h^{3\alpha+3}} \quad 7.7$$

Where  $h = H(D)/H_{ref}$ .

Overall, the increase in height results in increased energy capture, some of which can be realised by higher rated generators and the remainder results from higher capacity factors at the same rated power. Coulomb and Neuhoﬀ (2006), when estimating turbine costs assumed that 30% of increased wind energy capture with higher towers is used to increase the power rating by installing bigger generators per swept area. The remaining 70% of the additional energy captured at higher hub heights is concealed in the capacity factor and is not reflected in the turbine rating or turbine price. For COE based estimations, the proportion of improvement due to the capacity factor has more relevancy. It is therefore assumed that any change in ICC due to height is estimated by normalising the cost with a scaling exponent of  $H$  equal to  $(3*\alpha*0.3)$  and the extra change in the AEP due to improved capacity factors with height is represented by a scaling exponent of  $H$  equal to  $(3*\alpha*0.7)$ .

The scaling factors,  $a=1$  or 2 or 3, as suggested by Coulomb and Neuhoﬀ (2006) are based on theory for a standard turbine with each component based on one single cost driver. However in reality, components can have different cost drivers and the impact of innovation can alter the scaling exponents. Moreover, turbine components are complex being made up of different constituents, which in some cases have different scaling exponents. Exponents over 3 are also possible for large MW turbines due to bending moments as the diameter is increases. Instead of specifying scaling exponent as 1, 2 or 3, variables  $a_1, a_2, a_3, \dots, a_n$  are used. The variable  $n$  is the number of all possible scaling exponents for the turbine or component.

The weight CER is then given by:

$$W_{(D)} = W_{ref} \sum_{i=1}^n x_{wi} r^{a_i} \quad 7.8$$

Where  $x_{wi}$  is the proportion of weight of all components that scale with  $D$  to the power of  $a_i$ . To reduce complexity, if it is assumed that that all the cost is variable with weight ( $\mu = 1$ ), the resulting CER becomes:

$$C_{(D,H)} = C_{ref} \frac{\sum_{i=1}^n x_i r^{a_i}}{r^c h^d \eta_*^e} \quad 7.9$$

$$\text{Where: } r = D/D_{ref} \quad h = H/H_{ref} \quad \eta_* = \eta/\eta_{ref}$$

The parameters for the scaling models for weight and cost are summarised in table 7.2

|                                |  |
|--------------------------------|--|
| <b>Reference values</b>        | <p><math>C_{ref}</math>: 2 MW reference turbine or its component costs, ICC or COE from market data or modelled by detailed engineering costing methods.</p> <p><math>W_{ref}</math>: Reference turbine weight estimated using the Sunderland based engineering assessment models.</p> |
| <b>Scaling Exponents</b>       | <p><math>a_i</math>: Weight and cost scaling exponents for components</p> <p><math>c</math>: Power scaling exponent</p> <p><math>d</math>: Exponent representing increased yield at higher tower heights</p> <p><math>e</math>: Efficiency scaling exponent</p>                        |
| <b>Scaling Exponent Shares</b> | <p><math>x_r</math>: the proportion cost that varies with exponent <math>a_i</math></p> <p><math>x_{wi}</math>: is the proportion weight that varies with exponent <math>a_i</math></p>  |

**Table 7.2 Cost estimation relationships (CER) variables**

### 7.3.1 Parametric Factor

The parametric factors, modifying the reference values for cost or weight for any changes to the turbine or component due to scaling can be derived from Equations 7.8 and 7.9 and are given in Equations 7.10 and 7.11.

$$\text{Parametric Factor (weight)} = \sum_{i=1}^n x_{wi} r^{a_i} \quad 7.10$$

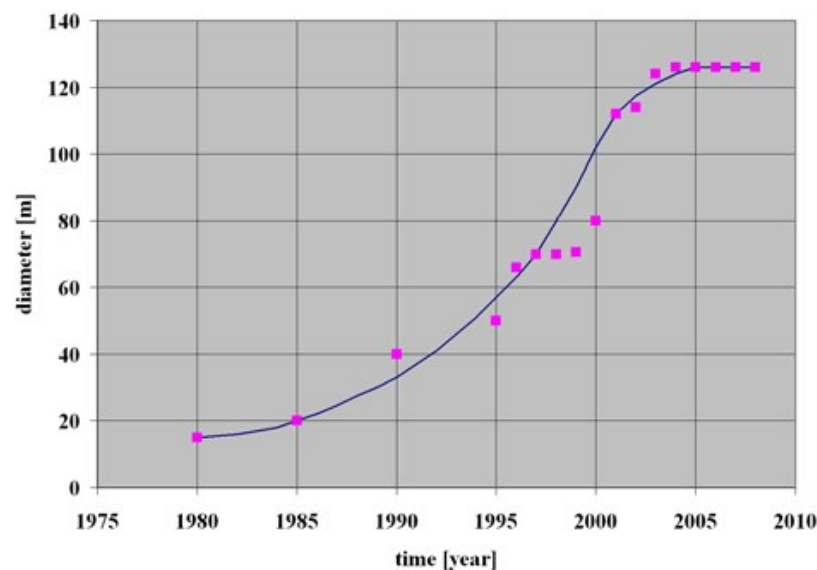
$$\text{Parametric Factor (cost)} = \frac{\sum_{i=1}^n x_i r^{a_i}}{r^c h^d \eta_*^e} \quad 7.11$$

To parameterise COE all factors in the numerator and denominator are relevant and the  $C_{ref}$  is the 2 MW reference turbine COE in €/MWh. For ICC estimations,  $C_{ref}$  is the 2 MW reference turbine ICC and the denominator is equal to 1 or  $r^c$  for normalised ICC/MW. For turbine or turbine component cost estimation the denominator is equal to 1 and  $C_{ref}$  is the cost of turbine or components.

The parametric factor is therefore a simple expression in terms of  $D$  that modifies the reference turbine cost to take account of diameter changes provided the turbine geometrical design is maintained as the size increases. Otherwise the detailed models

for the reference turbine would need to be adjusted first to take into account design changes additional to upscaling. For any cost component such as the turbine cost or COE, parametric variables such as the cost shares ( $x_i$ ) and scaling exponents ( $a_i$ ) can be derived from the reference turbine engineering assessment results. This results in an expression in terms of  $D$  only, and for any  $D$ , the mathematical expression can be solved to give a value that can be multiplied with the reference turbine values to give the cost or weight of the turbine at  $D$ . This will only apply provided the parametric variables ( $x_i$ ,  $a_i$ ,  $h$ ,  $c$ ,  $d$ , and  $e$ ) remain the same as  $D$  changes.

It then becomes important to consider the range of turbine size with which the parametric factors can be used with confidence to modify for the change in diameter. The assumption is that within this range the turbine design does not vary much as the turbine size increases. The current trend in the largest MW turbines has seen the power rating change from around 4 MW to 7.5 MW with a relatively low rate of change of the diameter as can be seen by curve of the changes in diameter for the largest MW turbines on the market in Figure 7.1.



**Figure 7.1** Turbine diameter growth (Gardner, Garrad et al., 2009).

It is therefore important to use a range of  $D$  that is not too wide so as to preserve the validity of the model. For modelling incremental change, it is assumed that all

turbines on the market have upscaled over the years. To ensure validity of the model it is generally assumed that the turbine upscaled from 80 m to about 130m typical with the current turbines on the market in the range of 5 MW. The design of large turbines is very sensitive to weight reduction measures, as can be seen by the flattening of the curve in Figure 7.1 from the early 2000s onwards. This affects the scaling exponents for very large turbines greater than 5 MW and therefore should be treated with caution. However, research efforts in the development and deployment of very large turbines continues with proposed future developments for turbines of up to 200m possibly in the range 10 to 20 MW. (Hendriks, 2008; UPWIND, 2012). For historical trend analysis downscaling to 40m, the average turbine diameter around the year 1990 will also be considered. Downscaling to the 20m diameter turbine of 1980 might result in distorted results.

### 7.3.2 Parametric Factor Variables

The parametric factors for both weight and cost are simplified and defined by the scaling exponent ( $a$ ) and the total share of the components with that scaling ( $x$ ). The estimation of these 2 variables for any component will allow the estimation of weight and cost at a given diameter ( $D$ ) relative to the reference turbine values. These variables are derived from the results of the reference turbine engineering assessment and are compared to other values from other sources to give confidence in their use.

#### Scaling Exponent Shares ( $x_i$ , $x_{wi}$ )

Table 7.3 gives the weight and cost shares ( $x_{wi}$  and  $x_i$  respectively) for the reference turbine based on the detailed engineering assessments results and are also compared to other sources. It is assumed that these shares will remain constant as the turbine size increases or decreases within reasonable limits.

| Component            | 2 MW Reference Turbine Results | Reference Turbine |               | Cost (%) (Jamieson, 2011) % | Cost (%) (Aubrey, 2007; Krohn et al., 2009) |
|----------------------|--------------------------------|-------------------|---------------|-----------------------------|---|
|                      | Weight (%)                     | Low Cost (%)      | High Cost (%) |                             |   |
| 3 Blades             | 7.6                            | 17.0              | 15.3          | 19.30                       | 24.7  |
| Hub                  | 5.9                            | 7.8               | 8.6           | 2.45                        | 1.5   |
| Pitch Mechanism      | 1.2                            | 5.0               | 4.8           | 6.4                         | 3.0   |
| Bedplate             | 9.7                            | 8.7               | 9.9           | 3.33                        | 3.1   |
| Nacelle covering     | 2.8                            | 2.3               | 2.8           | 2.45                        | 1.5   |
| Yaw Mechanism        | 1.6                            | 3.6               | 3.2           | 2.98                        | 1.4   |
| Shaft                | 1.6                            | 3.7               | 3.4           | 2.98                        | 2.1   |
| Bearings             | 0.4                            | 0.9               | 0.8           | 2.98                        | 1.4   |
| Gear Box             | 5.8                            | 13.3              | 12.0          | 17.00                       | 14.3  |
| Mech Equipment       | 1.2                            | 4.3               | 3.1           | 2.63                        | 2.7   |
| Generator (DFIG)     | 2.0                            | 5.5               | 5.0           | 6.66                        | 3.8   |
| Power Converter      | 0.4                            | 1.5               | 1.4           | 5.43                        | 5.6   |
| Electrical Equipment | 2.9                            | 7.1               | 6.5           | 9.64                        | 6.5   |
| Tower 85 m           | 57.0                           | 19.2              | 23.1          | 15.78                       | 29.2  |

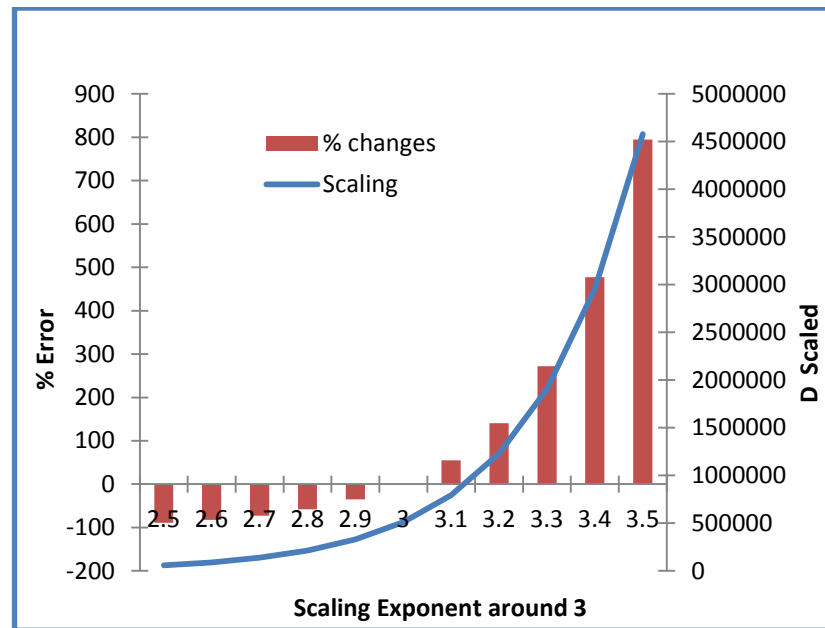
**Table 7.3      2 MW reference turbine weight and cost shares**

### Scaling Exponents ( $a_i$ )

Existing upscaling models are based on the square cubic laws in which weight scales as the cube of the diameter or radius whereas power output scales as the square of the diameter or radius of the turbine (Manwell, McGowan et al., 2002; Coulomb and Neuhoﬀ, 2006; Hau, 2006). The cost is considered to scale linearly with weight or mass. Laws such as these are sometimes known as rules of thumb and laws of similarity (DNV/Risø, 2002). These are of great importance in the initial stages of design for rough estimations when data is limited. However, such simplified rules can lead to high errors.

The use of the square-cube law gives a rough idea of the behaviour of cost, weight, power and yield as the sizes increase and a number of studies on turbine weight and costs are based on these laws. However the use of rounded oﬀ scaling results in errors and as these factors are used as powers the magnitude of the errors is significant. Figure 7.2 illustrates the magnitude of errors for the reference turbine

diameter of 80 m when a scaling to the power of 3 ( $D^3 = 512,000$ ) is used for assessment when in reality the scaling is in a range between 2.5 and 3.5.

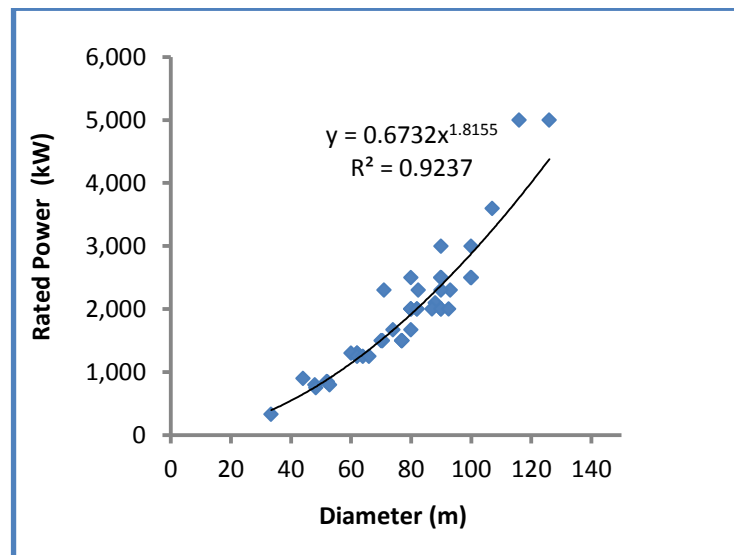


**Figure 7.2** Magnitudes of errors in scaling exponents

For example, the use of the cubic function (3) instead of a scaling exponent of 3.1 results in an error of 55%. The error magnitudes are higher if the values are larger than the theoretical 3 than the cases if less than 3.

Whilst wind turbine models have converged in the mainstream design, some innovations re-open issues around the optimisation. Innovation has the tendency to disrupt scaling behaviour as described by theory. Design improvements such as the use of lighter materials and part reduction result in lighter designs whose weight and cost scale less than the theoretical 3 (Thresher and M.Robinson, 2008). Design optimisation of the rotor blades and their material also allows for the use of larger diameters resulting in rated power ( $P$ ) scaling exponents that are less than 2. A trade off between the cost of longer blades and the increased energy capture determines the scaling of rated power. This study uses a scaling of 1.8 for the rated power typical with commercial data as shown in Figure 7.3.

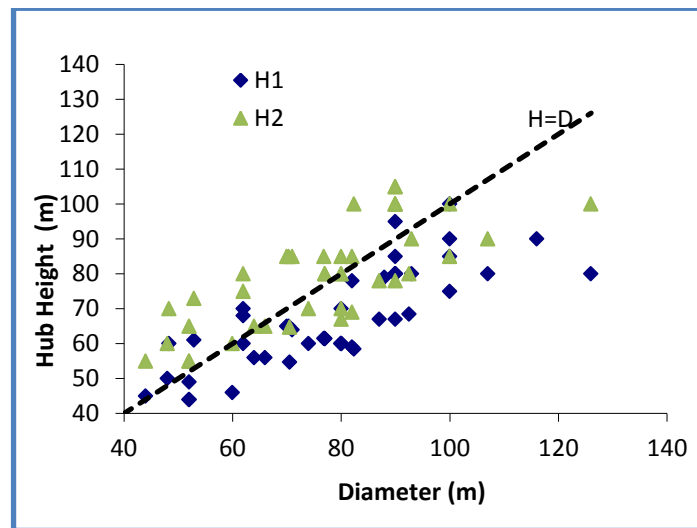




**Figure 7.3** Scaling of commercial turbines rotor diameter. (BWE, 2010)

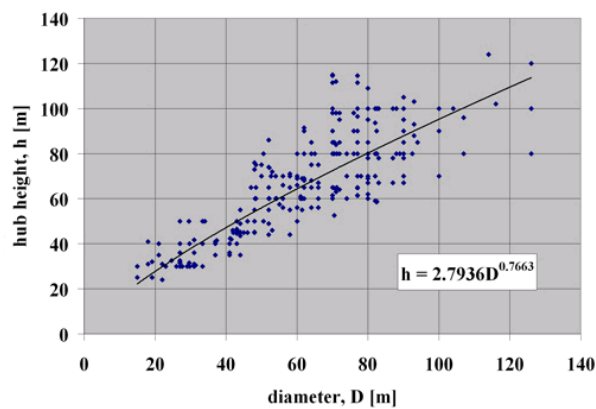
The increase in diameter,  $D$ , of turbines on the market is associated with an increase in rated power  $P$ . However, manufacturers also have models with larger diameters for the same power rating optimised for low speed sites. For example, the Vestas V90 has the same power rating as the V80, but has a diameter of 90 m. Similarly REpower has two 2 MW turbines models, the MM82 and the MM92 with diameters 82 m and 92 m respectively. A 23% increase in blade weight from MM82 to MM92 results in approximately an 18% increase in AEP (BWE, 2010). It is however cheaper to increase the yield by increasing the hub height  $H$  because an increase in  $H$  implies an increase in the wind speed which scales with power with an exponent of 3 whereas  $D$  scales with an exponent of 2. Moreover, compared to the tower, the blade is more expensive than the tower in terms of material and manufacturing. The increase in the blade length also has a negative impact of increasing the rotor weight and hence the cost of other components such as the nacelle. It is assumed that  $D$  remains the same for a given rated power to simplify the model.

Historically, the typical trend for the turbine hub height  $H$  is that it is approximately equal to the diameter  $D$ , but larger turbines have a height less than the diameter. A trade off exists between tower weight cost and the increased energy capture at higher heights. Figure 7.4 is a plot of the relationship between  $H$  and  $D$  for global MW turbines.



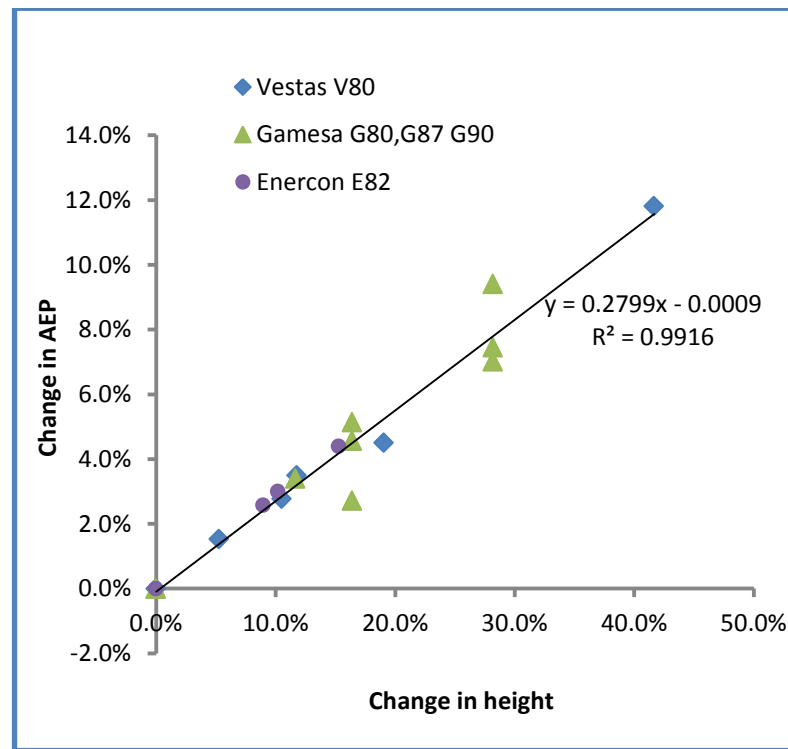
**Figure 7.4** Rotor diameter vs. Height trend for commercial turbines. (BWE, 2010; WEM, 2012)

Moving from left to right as the diameter increases more turbines lie below the  $D = H$  line so as to reduce tower costs. The relative lower costs of increasing the tower height compared to costs of increasing blade diameter allow turbine manufacturers to design turbines with options of higher hub heights.



**Figure 7.5** Hub height scaling. (Gardner, Garrad et al., 2009)

For this study, a scaling exponent of  $H$  with  $D$  of 0.7 is used similar to NREL studies (Fingersh, 2006) and typical of commercial turbines as shown in the plot in Figure 7.5. The relationship between the increases in height and the resulting increases in yield for major 2 MW turbines are shown in Figure 7.6.



**Figure 7.6** Yield (AEP) increases with Hub Height ( $H$ ). Data source Germany Wind Energy association (BWE, 2010)

Generally, a 20% increase of the height results in about a 5% increase in the yield. The increase in tower costs corresponding to an increase of the hub height  $H$  from 60 m to 85 m is estimated at 16% of the turbine cost, but only 1.8% of ICC.

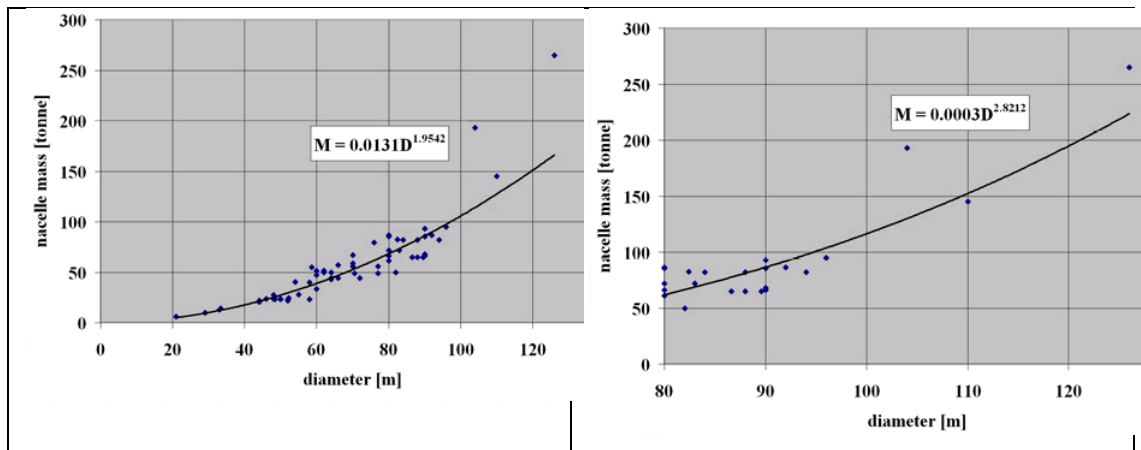
The increase in energy capture due to increased hub height or due to longer blades results in improved scaling exponents of the yield or the annual energy production (AEP). The increase in energy capture at higher hub heights is captured using the relationship between velocity and height given in equation 5.2.

### 7.3.3 Scaling Turbine Components

As discussed earlier, the turbine is made up of a number of components with different materials and parts, hence variations in scaling exponents. Technological developments of components also result in varying scaling factors for different components and for the whole turbine. Weight reduction efforts and other design optimisation strategies have resulted in lower scaling exponents. Vestas claimed its 3 MW turbine towerhead weight is identical to that of the 2 MW design towerhead

weight due to design improvements though the 3 MW rotor radius is 5m longer than the 2 MW (EU, 2005). Blade weight reduction is important because it results in weight reduction of other components such as hub, nacelle and tower structure (Sahin, 2004).

A given value of a scaling exponent is valid for specific ranges of size, beyond which different values apply. This is illustrated by a plot of nacelle weight (with drivetrain equipment) and is shown in Figure 7.7 for turbines with a diameter ( $D$ ) below 80 m (left) and turbines above 80 m (Gardner, Garrad et al., 2009).



**Figure 7.7** Nacelle weight scaling for turbines with  $D < 80$ m (left) and  $D > 80$ m (right) (Gardner, Garrad et al., 2009)

The scaling exponents for this study are obtained from the detailed assessment models used to estimate the weight of turbine components in Chapter 5. The parametric factors for the components and the subsystems are derived using these exponents and the shares for the exponents and for the components. The resulting parametric factors are given in the section below before the cost and weight results.

## 7.4 Upscaling Results

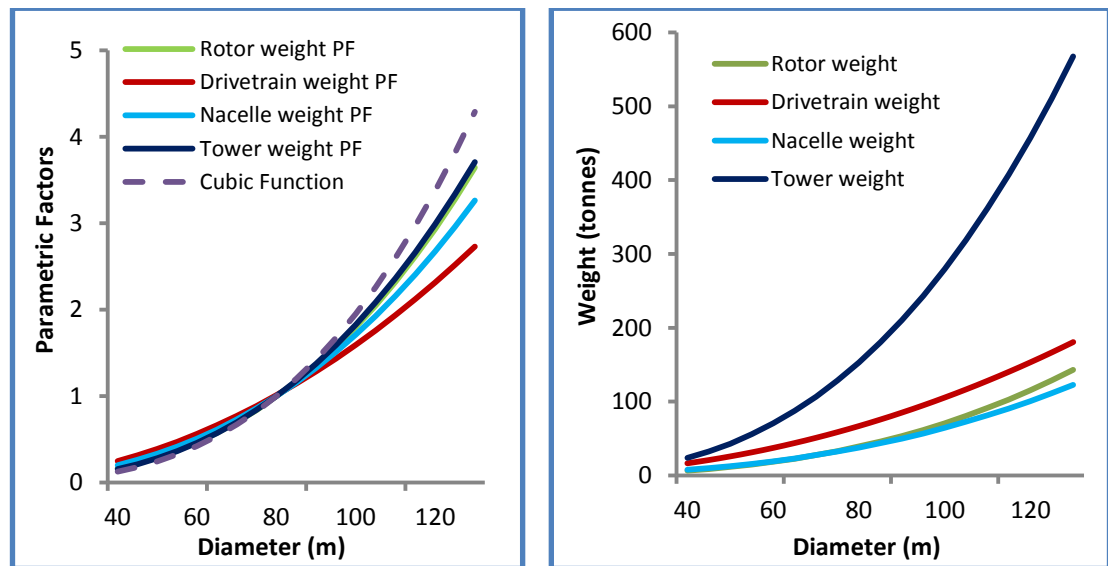
Table 7.4 gives the resulting weight parametric factors (PF) from the method described in the section above. The scaling exponents were derived from the Sunderland based model equations used for weight estimation given in Section 5.4.

| Component          | Parametric factor  |
|--------------------|--|
| 3 Blades           | $PF_{BL} = 0.36r^{2.00} + 0.12r^{2.70} + 0.52r^{3.00}$   |
| Hub                | $PF_H = r^{2.64}$  |
| Pitch Mechanism    | $PF_{Pmech} = r^{3.00}$  |
| Bedplate           | $PF_{N-BP} = 0.49r^{2.00} + 0.19r^{2.60} + 0.32r^{3.00}$   |
| Nacelle covering   | $PF_{N-CL} = r^{2.00}$   |
| Yaw Mechanism      | $PF_{N-YM} = 0.76r^{3.00} + 0.24r^{2.00}$  |
| Shaft              | $PF_{Shaft} = r^{2.88}$  |
| Bearings           | $PF_{Bearngs} = r^{2.50}$  |
| Gear Box           | $PF_{GearB} = r^{3.00}$  |
| Mech Equipment     | $PF_{Mech Equip} = r^{2.00}$   |
| Generator          | $PF_{Generator} = r^{2.00}$  |
| Partial PE         | $PF_{Pwr Electronics} = r^{2.00}$  |
| Electric Equipment | $PF_{Elec Equip} = r^{2.00}$   |
| Tower ( H = 85 m)  | $PF_{Tower} = r^{2.70}$  |
| Total turbine      | $PF_{Turb} = 0.17r^{2.00} + 0.004r^{2.50} + 0.18r^{2.60} + 0.059r^{2.64} + 0.579r^{2.70} + 0.16r^{2.88} + 0.153r^{3.00}$ |

**Table 7.4 Turbine Parametric Factors**

Scaling exponents for the blades from other sources include 2.86 (Hendriks, 2008), 2.87 (Griffin, 2001), 2.53 NREL Advanced (Fingersh, 2006) and 2.2892 (Jamieson, 2004). Jamieson (2004) also states a scaling of 2 for the shaft.

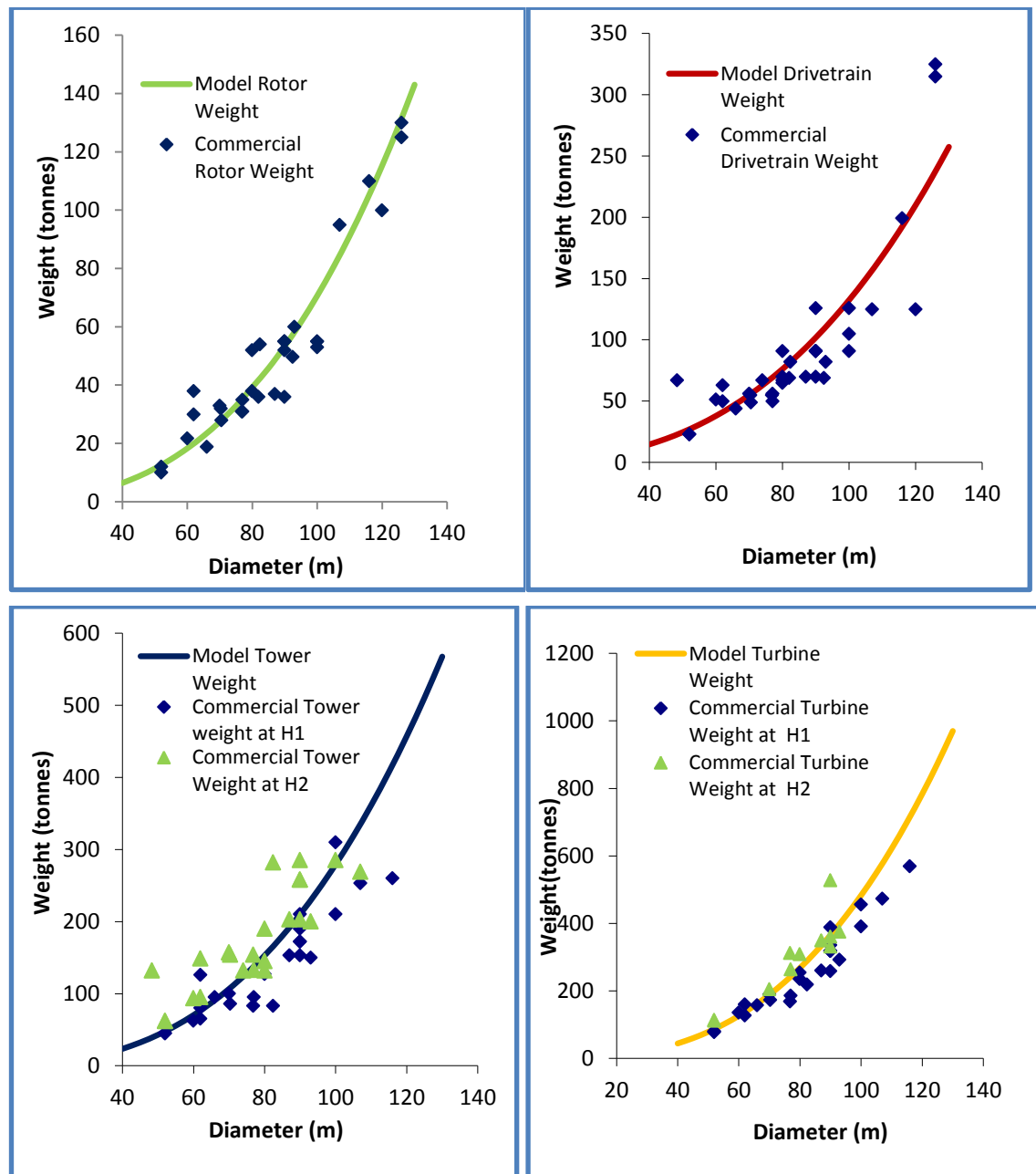
The same scaling exponents used for weight parametric factors for each component or subsystem are also used for the cost parametric factors. The difference is in the cost shares which differ from the weight shares as given earlier in Table 7.3. Figure 7.8 shows a plot of the parametric factors of weight and resulting weight for a range of diameters for the turbine subsystems.



**Figure 7.8 (a) Parametric Factors, (b) Weight of the 2 MW reference turbine subsystems**

The rotor and tower weights increase at a faster rate than the nacelle and drivetrain, but they all scale with functions less than the cubic function. The drivetrain weight rate of increase is the lowest because most of the components scale with an exponent around 2 due to power rating ( $P$ ) having the major influence. The combination of the tower's high scaling exponent of 2.7 and the high reference weight (57% of the total weight) makes the turbine weight at any height very high. Although the drivetrain has the lowest parametric factor, its weight is higher than the weight of the nacelle and the rotor because of the high weight of the reference turbine drivetrain.

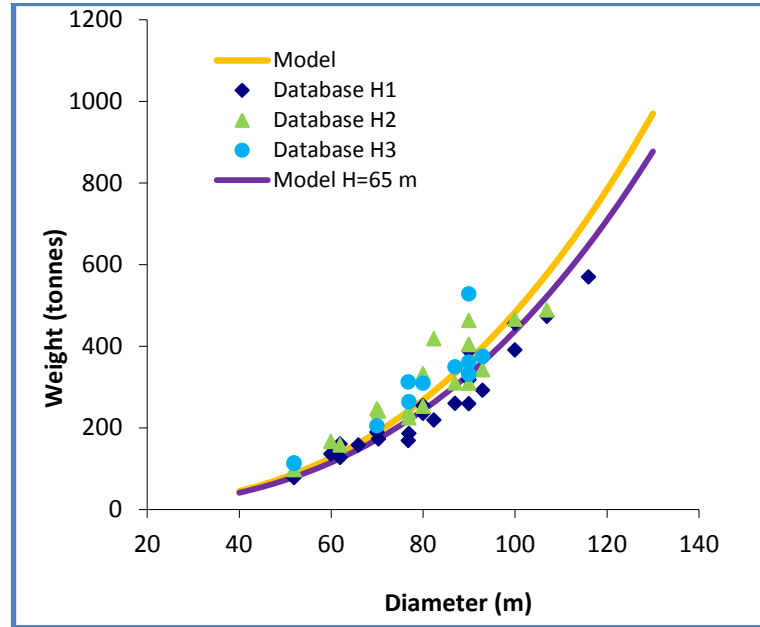
Figure 7.9 gives plots of the model results for subsystem weights plotted with weight market data from German websites that collect wind turbine global data (BWE, 2010; WEM, 2012).



**Figure 7.9 Comparison of parametric model upscaling results for the 2 MW reference turbine with commercial database (BWE, 2010; WEM, 2012).**

The subsystem weight models plot well with market data. The data plotted in Figure 7.9 is not for the average turbine height but the first or lowest height specified for each model plotted. On the other hand the reference height ( $H_{ref}=85$  m) is not on the lower end for the Vestas turbine. The fit for the tower and turbine (a) and (b) in

Figure 7.9 is improved by including another set of turbine heights for the market data,  $H_2 > H_1$ . The fit for the turbine weight is further improved in Figure 7.10 by including model results for  $H_{ref} = 65$  m and including another set of heights for the market data,  $H_3 > H_2 > H_1$ .



**Figure 7.10 Turbine Total Weight Results**

## Cost Results

The resulting parametric factors for the turbine costs are shown in Table 7.5.

| Component            | Share | Parametric Factor  |
|----------------------|-------|--|
| Rotor                | 0.30  | $PF_{Rotor} = 0.20r^{2.00} + 0.30r^{2.64} + 0.06r^{2.70} + 0.45r^{3.00}$   |
| Nacelle              | 0.15  | $PF_N = 0.51r^{2.00} + 0.11r^{2.60} + 0.38r^{3.00}$  |
| Drivetrain           | 0.36  | $PF_{DriveTr} = 0.45r^{2.00} + 0.03r^{2.50} + 0.14r^{2.88} + 0.37r^{3.00}$   |
| Tower                | 0.19  | $PF_{Tower} = r^{2.70}$  |
| Drivetrain + Nacelle | 0.51  | $PF_{N\&DT} = 0.52r^{2.00} + 0.01r^{2.50} + 0.03r^{2.60} + 0.07r^{2.88} + 0.36r^{3.00}$                              |
| Total                | 1.00  | $PF_{Turb} = 0.33r^{2.00} + 0.01r^{2.50} + 0.02r^{2.60} + 0.06r^{2.64} + 0.19r^{2.70} + 0.04r^{2.88} + 0.33r^{3.00}$ |

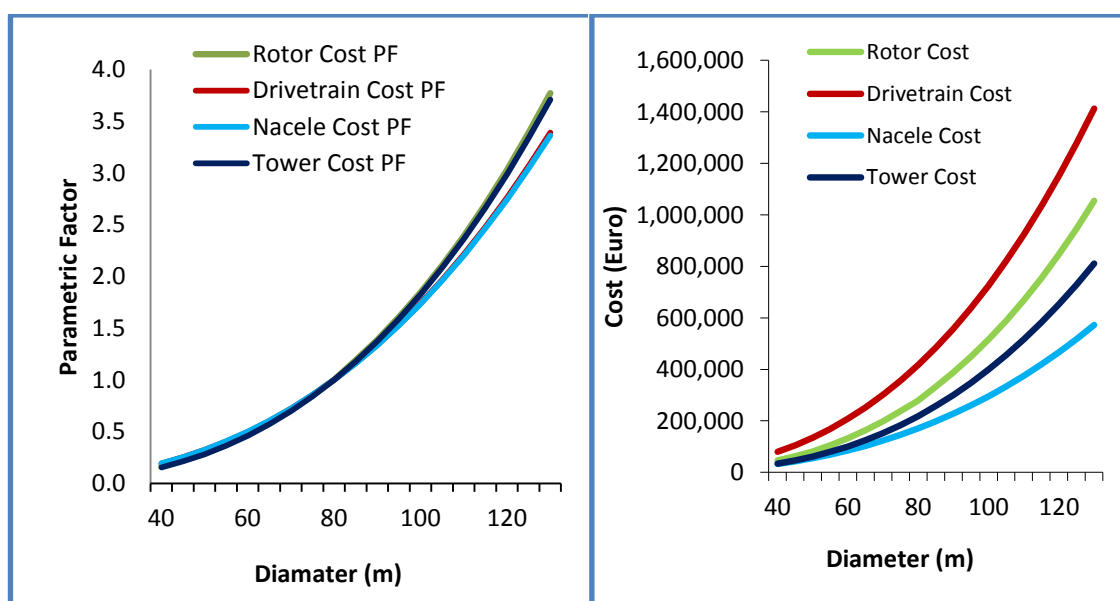
**Table 7.5 Turbine Subsystems Parametric Cost Factors for the DFIG turbine**



The results in Table 7.5 show that only 33% of the turbine scales with a scaling exponent of 3 instead of 100% as implied by the square cube law. The scaling of the turbine (exponent of 2.7) is significant for the weight of the whole turbine because the tower constitutes 57% of the turbine weight.

The major difference in the weight and cost parametric factors is in the weight and cost proportions of the components and subsystems. This has an impact on the weight shares for the different exponents. For example the 45% of the rotor cost scales with an exponent of 3 whereas 35% of its weight scales with an exponent of 3.

The parametric cost factors and actual cost for the turbine and its subsystems for diameter in the range 40m to 130m are plotted in Figure 7.11. The cost plot shows the resulting cost as the turbine diameter changes whereas the parametric factor trend shows the rate at which the cost changes.



**Figure 7.11 Cost Parametric Factors and Cost Results (Low Cost Range) for the turbine subsystems.**

The parametric factors of the four subsystems scale at nearly the same rate as the turbine diameter increases. The rotor and the tower have slightly higher parametric factors than the other two. The near similar relationships are due to a combination of a number of factors such as the cost shares and the respective specific costs. The

heavy tower, though relatively cheaper, maintains a high rate of increase in cost because it scales by the same relatively high exponent of 2.7 as that for the weight. In contrast, the tower cost trend is much lower than the rotor and the drivetrain because of the tower's low specific costs. The drivetrain is made up of many complex electrical, mechanical and electronic components. The relative specific costs result in drivetrain costs with higher scaling trends than the parametric factor scaling trend, which is low because the majority of drivetrain components scale with exponents near 2. It can also be observed from Figure 7.11 that the cost of the blades is also relatively higher than the tower weight because blades are a specialised component relatively expensive to manufacture.

Overall, it should be noted that although the tower weight is high and increases at a fast rate, the drivetrain is the most critical subsystem in terms of turbine costs. In addition, the reliability of the turbine is reduced because of high failure rates in the drivetrain components, in particular the gearbox. For turbines greater than 5 MW this becomes more pronounced and calls for an alternative drivetrain design. The tower is also critical because of the heavy weight. However, its specific costs are low and it is relatively easier to manufacture. It becomes a concern for balance of station (BOS) costs and transport costs.

The parametric factors for the BOS were derived from the models used to estimate the cost in the previous chapter given in equations 6.3 to 6.8. Table 7.6 shows the distribution of the BOS and the ICC.

| Scaling Exponent ( $a_i$ ) | 1.10 | 1.21 | 2.00 | 2.35 | 2.50 | 2.60 | 2.64 | 2.70 | 2.88 | 3.00 |
|----------------------------|------|------|------|------|------|------|------|------|------|------|
| Turbine PF                 |      |      | 32.2 |      | 0.9  | 1.7  | 7.8  | 21.2 | 3.7  | 32.6 |
| BOS                        | 8.6  | 12.5 | 66.9 | 11.9 |      |      |      |      |      |      |
| ICC                        | 2.4  | 3.5  | 41.9 | 3.3  | 0.7  | 1.2  | 5.6  | 15.3 | 2.7  | 23.5 |

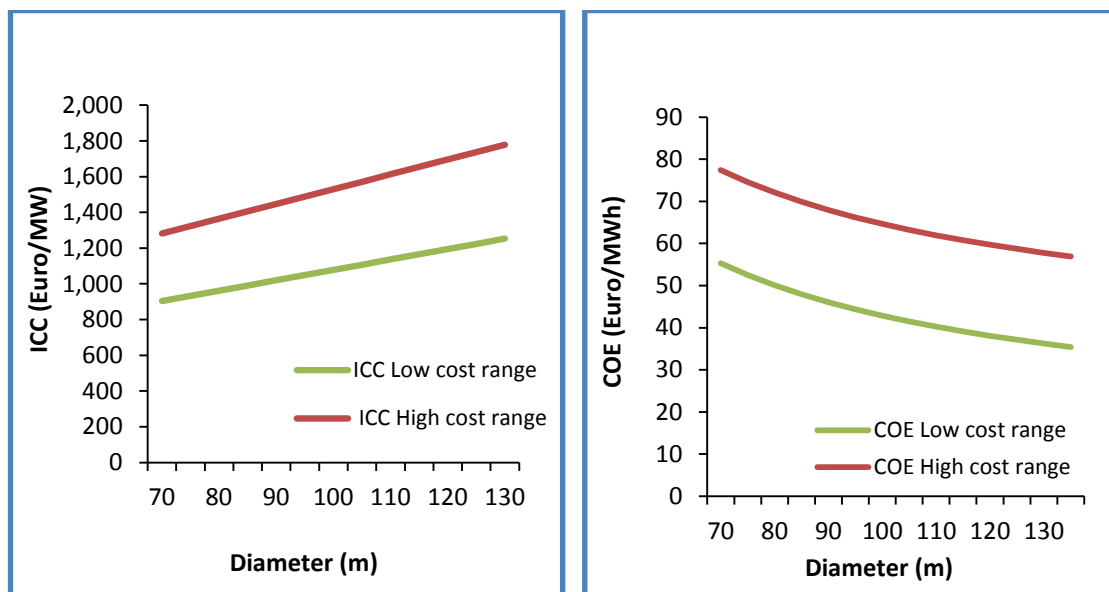
**Table 7.6 BOS and ICC scaling exponent shares ( $x_i$ ) as a percentage**

The BOS scales with relatively low scaling exponents between 1.10 for the foundation and 2.35 for assembly. This factor combined with the fact that the BOS

cost makes up just 25% of the ICC makes the turbine cost a more critical cost centre for the capital costs as the turbine is upscaled for onshore wind. This is in contrast with offshore wind energy as will be discussed in Section 9.3.

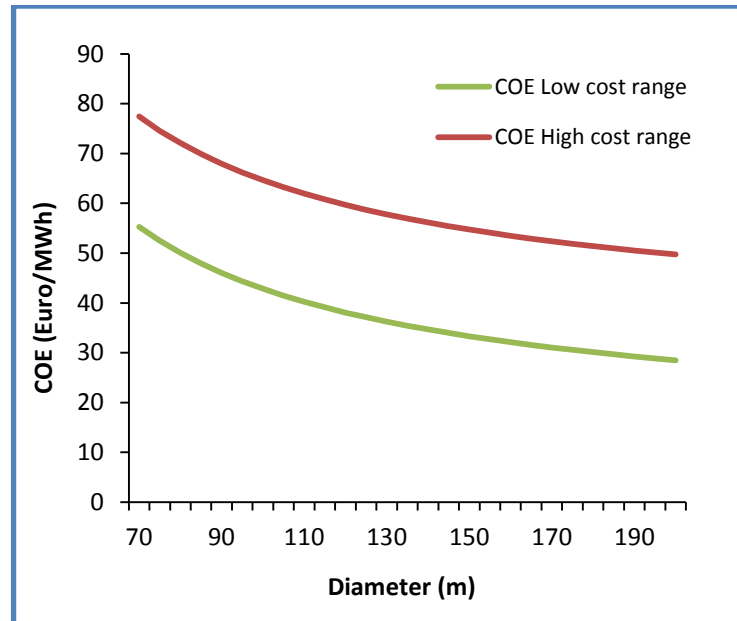
The COE parametric factors are derived using the ICC parametric factors and the impact of the capacity factor improvements due to increases in height discussed earlier is factored in using the scaling exponent ( $d = 3 \cdot 0.7 \cdot \alpha$ ). For  $\alpha = 1/7$  for onshore turbines, approximately the exponent  $d = 0.3$ . The design of larger turbines is associated with efforts to improve the performance of the turbine and its components. To simplify the model it is assumed that the yield increases linearly with size due to overall efficiency and reliability improvements. Therefore the term  $\eta^e$  in equations 7.9 and 7.11 is replaced with the term  $r^e$  and simply  $e = 1$ . The resulting parametric factor is therefore expressed only in terms of the relative diameter  $r$ .

Figure 7.12 shows a plot of the results for the ICC and the COE for both low and high costs compared to constant reference values for all sizes of the turbines.



**Figure 7.12** ICC and COE Upscaling Results based on the reference turbine and the parametric factors in Table 7.6.

Figure 7.13 is a plot of the COE when extrapolated to larger diameters for larger turbines in the range 10 MW to 20 MW.



**Figure 7.13 Upscaling COE Results**

Theoretically, the COE for turbines with large diameters of up to 200m can reduce to nearly 30 €/MWh provided all technical barriers associated with upscaling very large turbine are overcome.

## 7.5 Modelling Radical Change

The direct drive (DD) system considered is based on the synchronous generator DDSG used by the leading DD manufacturer Enercon. The removal of the gearbox and the replacement of the generator is considered radical at component level.

The modelled results of the reference turbine show that the gearbox is a significant turbine component constituting 6% of the total turbine weight and 13% of the cost and has an impact on other components such as the bearings. The assessment of the DD therefore requires changes to the detailed assessment models of the 2 MW reference turbine resulting in new values for  $C_{ref}$  and  $W_{ref}$  for the affected components and the whole turbine. Direct drive turbines have been on the market

since the 1990s and the turbine concepts have also experienced upscaling. Enercon turbines on the market range from 800kW to 7.5 MW (Enercon, 2012). The DD concept is also modelled parametrically to account for changes in the diameter

Direct drive turbines have gained increasing popularity in recent years due to the low reliability and high maintenance costs of gearbox components. The direct drive configuration has fewer moving parts and therefore can reduce maintenance costs and provide higher wind turbine availability. The removal of the gearbox reduces the length of the drivetrain hence the length of the nacelle which has significant weight reduction impact. Long drivetrains have lower natural frequencies therefore in addition to weight and cost short drivetrains have a definite advantage (Hau, 2006).

For a direct drive system, the generator is the largest contributor to the overall drivetrain mass and there is big difference in the mass of a DFIG and a direct drive synchronous generator. Due to the lack of a gearbox, direct drive generators must operate at much lower rotational speeds thus requiring the generator to be larger and more robust to handle the increased torque loads (Maples, Hand et al., 2010). Low speed direct drive generators have more poles, hence are larger, heavier and more expensive. Higher cost of the low speed generator in direct drive systems may be equal or reduced by avoided gearbox cost.

The main two DD concepts are the electrically excited synchronous generator system DDSG and the direct drive permanent magnet synchronous generator (PMSG). In terms of power density the DDSG is the less favourable option, even though it dominates the direct drive share of the market. Enercon, one of the top ten global turbine manufacturers has been manufacturing this drivetrain concept with a significant market share of the global market. Enercon claims benefits from the system in the performance and reliability of the turbines. (Polinder, Van Der Pijl et al., 2006; Enercon, 2012).

The alternative synchronous generator concept, the PMSG, is much more attractive because the active material weight of the generator for the same air-gap diameter is nearly halved, while the energy yield is a few percent higher (Polinder, Van Der Pijl et al., 2006; Li and Chen, 2008). However, compared to the conventional direct

generator, it is more expensive because of the high permanent magnet costs. Further improvements of this generator system may be expected because the cost of the permanent magnets and the power electronics are decreasing and because further optimisation and integration of the generator system is possible (Polinder, Bang et al., 2007b). As the DDSG had been the main concept on the market for years the modelling of DD for this study is mainly based on this concept.

### **7.5.1 Direct Drive Turbine Weight and Costs**

It is assumed that the rotor for the DD turbine is similar to non DD and there are therefore no changes to the weight and the cost to the rotor. The tower design also remains the same although there are significant towerhead weight changes, resulting in an impact on the tower weight. The impact of the change from gearbox to DD has a significant impact on the drivetrain and the nacelle.

The detailed analysis of the two subsystems is simplified by the fact that the assessment will be an upgrade of the 2 MW reference turbine models with simple changes in cost drivers, service factors or just specific cost for the affected components. Costing models will not be developed from scratch. The Sunderland model in Chapter 5 is used to estimate changes to the cost and weight of 2 MW reference turbine components for DD, and Table 7.7 summarises the changes.

| Component  | Turbine Weight and Cost changes  |
|--|--|
| <b>Gear Box</b>                                  | <b>Gearbox Elimination</b><br><br>Drivetrain weight reduced and turbine weight is reduced by 13% (15.7tonnes) due to this elimination. Costs are also reduced.   |
| <b>Generator</b><br><br><b>From DFIG to DDSG</b> | <b>Replacement of DFIG with DDSG</b><br><br>Larger generator, heavier and expensive. Less standard concept, therefore more costly. The weight of the DDSG is estimated at 50 tonnes compared to the DFIG 5 tonnes. The cost of the DD is estimated at €300,000                         |
| <b>Shaft</b>                                     | <b>Shorter Length</b><br><br>The shaft length service factor $F_{LSS}$ (Table 5.12) reduces from 1 to 0.6 for the compact drivetrain. Similarly the bearings system weight reduces by 40%.   |
| <b>Power Electronics</b>                         | <b>Full rated Power Converter</b><br><br>The replacement of the partial converter increases the weight by 100%.to 2tonnes and the cost from €18,000 to €100,000 (UPWIND, 2012)   |
| <b>Nacelle</b>                                   | <b>Compact drivetrain</b><br><br>Nacelle Cladding and bedplate weight is reduced. The bedplate factor $F_{BP}$ used for reduces from 1 to 0.5 and the bedplate length $F_{DR}$ reduces from 1 to 0.8. A factor of 0.7 is used to account for the change in the overall nacelle weight. |
| <b>O&amp;M costs</b>                             | <b>Annual Costs Reduction</b><br><br>O&M costs are reduced due to less downtime and this assumed to reduce the annual costs by 20%.  |
| <b>Turbine Performance</b>                       | <b>Improvements</b><br><br>The removal of the gearbox increases availability and turbine efficiency. It is assumed that the AEP increases by 5%. Modelling of the impact of design changes on the system efficiency is discussed below.  |

**Table 7.7      Design Changes for Direct Drive**

### 7.5.2 Modelling Drivetrain Efficiency

The efficiency can be analysed using efficiency curves which indicate the importance of efficiency especially at part loads. Because of the intermittency of wind, operation at part loads is common. The drivetrain efficiency model developed was derived in previous studies (Fingersh, 2006; Maples, Hand et al., 2010). The efficiency for the Drivetrain can be defined as:

$$\eta = \frac{P_{ratio} - (L_{const} - L_{lin}P_{ratio} + L_{quad}P_{ratio}^2)}{P_{ratio}} \quad 7.12$$

Where  $P_{ratio} = P/P_r$  and  $P_r$  is the rated power)

$L_{const}$  - constant losses,  $L_{lin}$  - linear losses,  $L_{quad}$  - quadratic losses.

*Constant losses* are independent of the power level. Transformer losses make up most of the constant losses and NREL studies reported that most suppliers quote transformer efficiency at 99.4% which translates to a 0.6% loss (Bywaters, John et al., 2005). *Linear losses* change linearly with the rate such as fan losses and switching losses in a converter and these are typically low. Linear losses of 0.2% for DFIG and 0.5% for DD because of the full rated power converter are assumed (Fingersh, 2006). *Quadratic losses* most common are copper losses which follow the  $I^2R$  formula at a constant voltage. This category also includes the iron losses as well as conduction losses in some gear types.

Other gearbox losses are also quadratic including lubrication losses in a variable speed gearbox among others. Gearbox efficiency depends on gearbox ratio, type of gear and viscosity of the lubricant. As a guide parallel shaft gears have approximately 2% losses per stage and planetary gear has approximately 1% losses per stage. (Hau, 2006). For the 2 DFIG reference turbine with two planetary (epicyclic) and one parallel (spur) the losses are approximated at 4%. In contrast, the DD systems eliminate all quadratic losses associated with the gearbox. However it has a small share of quadratic losses in order to keep the generator size small (Fingersh, 2006). Table 7.8 lists losses based on data from Polinder et al (2006) and

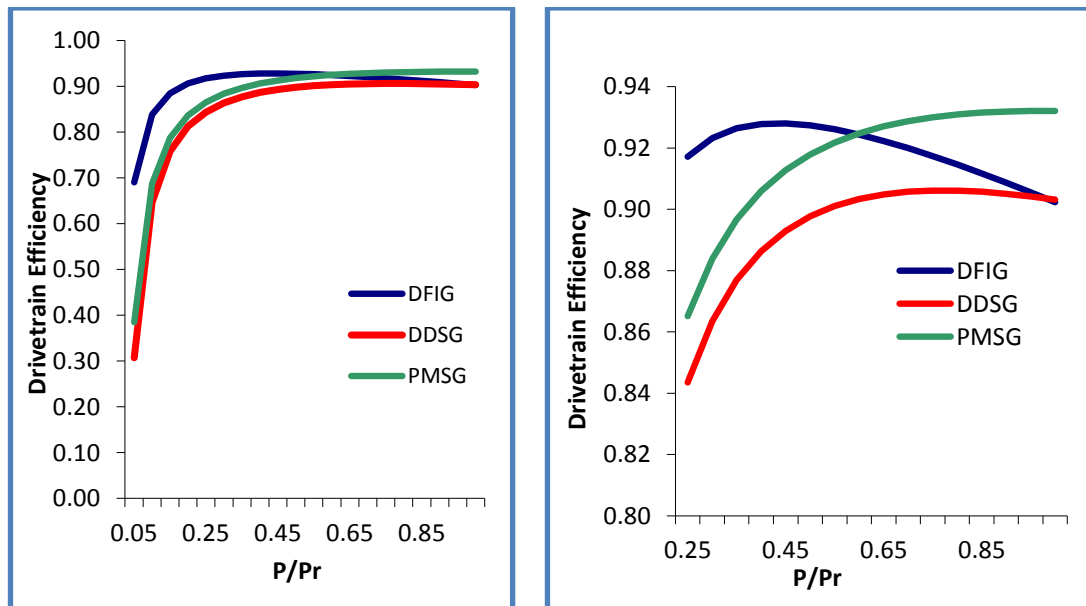


efficiencies are estimated using Equation 7.12. The permanent magnetic direct drive (DDPMSG) is also included for comparison.

|                     | Scaling | DFIG   |            | DDSG   |              | DDPMSG |            |
|---------------------|---------|--------|------------|--------|--------------|--------|------------|
|                     |         | (MWh)  | $\eta$ (%) | MWh    | $\eta$ (%)   | MWh    | $\eta$ (%) |
| <b>Copper</b>       | 2       | 52     | 0.96%      | 292    | 5.29%        | 121    | 2.21%      |
| <b>Iron</b>         | 2       | 45     | 0.83%      | 26     | 0.47%        | 57     | 1.04%      |
| <b>Converter</b>    | 1       | 50     | 0.92%      | 156    | 2.83%        | 150    | 2.74%      |
| <b>Gearbox</b>      | 2       | 341    | 6.27%      | 0      | 0.00%        |        |            |
| <b>Transformer</b>  | 0       | 33     | 0.60%      | 33     | 0.60%        | 16     | 0.30%      |
| <b>Linear</b>       | 1       | 11     | 0.20%      | 28     | 0.50%        | 27     | 0.50%      |
| <b>Total Losses</b> |         | 520.64 | 8.99%      | 507.12 | 8.59%        | 344.41 | 5.80%      |
| <b>Efficiency</b>   |         |        | <b>91%</b> |        | <b>91.4%</b> |        | <b>94%</b> |
| <b>Yield , GWh</b>  |         | 5.44   |            | 5.52   |              | 5.47   |            |

**Table 7.8 Drivetrain Losses and efficiencies estimated using data derived from (Polinder, Van Der Pijl et al., 2006)**

Figure 7.14 show the results for the different concepts for part load between 5% and 100% for (a) on the left and between the more likely to occur 25% and 100% for (b) on the right.



**Figure 7.14 Drivetrain Efficiency Curves (a) Part Load 5-100% and b) 25-100%, plotted using Equation 7.12 and Table 7.8.**

The second plot shows the efficiencies of the different concepts near full rating and the DFIG at low part loads has higher efficiencies but the DDSG becomes more efficient of quadratic losses which are high for the DFIG. The PMSG has higher efficiencies than DDSG but its detailed analysis is not covered in this study.

### 7.5.3 Direct Drive Cost and Weight Results

The DD cost and weight results are given in Table 7.9 and are compared to DFIG results for the 2 MW reference turbine.

|                           | <b>DFIG</b> | <b>DD</b> | <b>Change</b> | <b>% Change</b> |
|---------------------------|-------------|-----------|---------------|-----------------|
| Drivetrain Weight (kg)    | 38 542      | 65 981    | +27 439       | +71%            |
| Drivetrain Cost (€)       | 435 266     | 549 108   | +113 842      | +26%            |
| Turbine Weight (kg)       | 268 238     | 287 330   | +19 092       | +7%             |
| Turbine Cost (€)          | 1 205 905   | 1 280 168 | +74 262       | +6%             |
| Total Investment Cost (€) | 2 033 622   | 2 096 265 | +85 402       | +3%             |
| System Efficiency         | 0.910       | 0.914     | +0.004        | +0.5%           |
| AEP (MWh)                 | 5 256 000   | 5 518 800 | +262 800      | +5%             |
| COE low (€/MWh)           | 49.97       | 45.38     | -4.59         | -9%             |
| COE high (€/MWh)          | 73.47       | 67.41     | -6.0636       | -8%             |
| PMSG                      | 49.97       | 44.48     | -5.59         | -11%            |
| PMSG high                 | 73.47       | 66.03     | -7.4428       | -10%            |

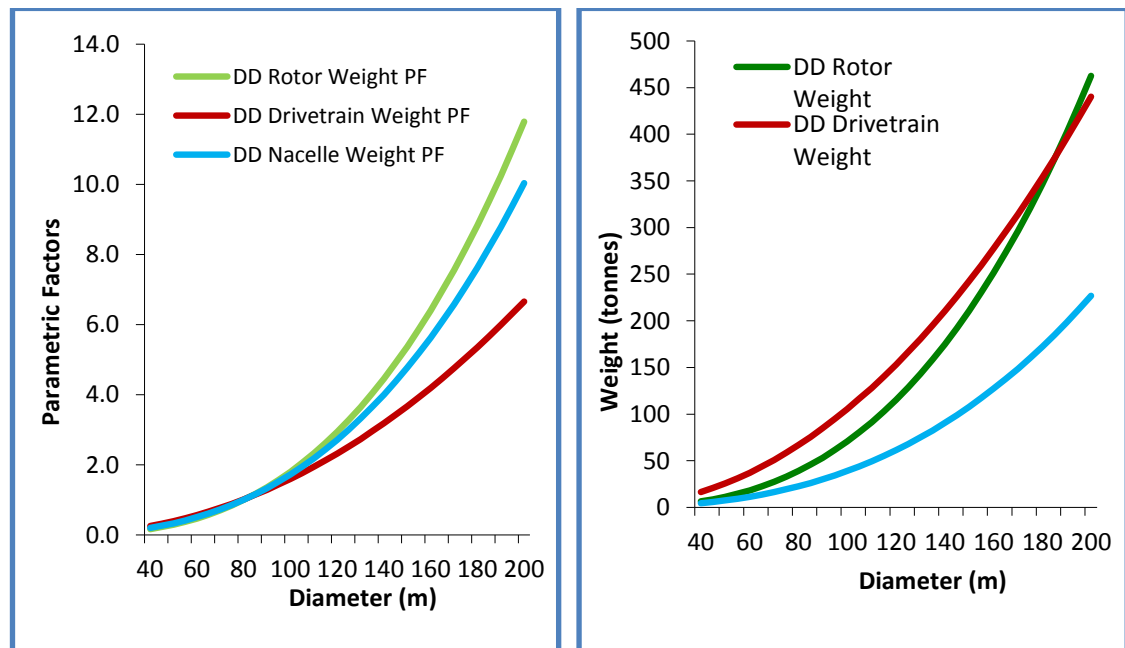
**Table 7.9 DD Detailed Costing Results**

Table 7.9, Column 4, gives the impact of change to the 2 MW reference turbine parameters caused by the move from DFIG to DD drivetrain system and column 5 gives the impact as a percentage. The move to DD increases the turbine cost by about 6% but the overall increase in performance result in 9% reduction in COE. Increases in the AEP have been found to have a greater impact on the COE than the turbine costs. If the efficiency for the DD is increased to 94% to roughly represent the PMSG, COE is reduced by 11%. This explains the trend towards DD especially for the larger MW turbines for offshore where reliability is a major issue despite the high capital costs. The annual energy production (AEP) for the DD is also modelled similar to the 2 MW reference turbine at the Dunstaffnage hypothetical windfarm

with the main difference in the system efficiencies. Section 7.5.4 uses the results to model the upscaling trend for DD concepts.

### 7.5.4 Direct Drive Upscaling

The same scaling exponents for the DFIG reference turbine are used for the DD turbine components. The removal of the gearbox however, changes the overall scaling exponents of the drivetrain. The other major changes are in the components shares to the total weight and costs.



**Figure 7.15 Weight Parametric Factors and Weight Subsystem Results**

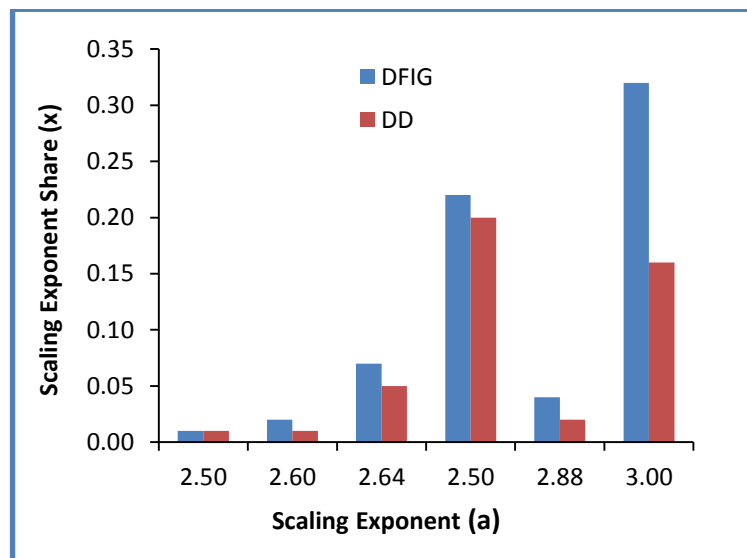
The parametric model for the DD are plotted on a wider range of diameters to 200m as this concept with continued research and development efforts is most likely to be used in very large turbines (Bywaters, John et al., 2005; Polinder, Bang et al., 2007). From Figure 7.15 it can be seen that the drivetrain PF trend is low. Although the generator is heavier than that in the DFIG, the eliminated gearbox scaled with an exponent of 3 whereas the replacing generator scales with a lower exponent of 3. For the weight the drivetrain weight dominates the turbine towerhead weight to around 175m where the rotor weight becomes more dominant.

Table 7.10 shows the parametric factors for the DD costs derived using the similar proposed method in Section 7.3.

| Component            | Share | Parametric Factor  |
|----------------------|-------|--|
| Rotor                | 0.28  | $PF_{Rotor} = 0.21r^{2.00} + 0.22r^{2.64} + 0.07r^{2.70} + 0.50r^{3.00}$   |
| Nacelle              | 0.10  | $PF_N = 0.48r^{2.00} + 0.11r^{2.60} + 0.41r^{3.00}$  |
| Drivetrain           | 0.44  | $PF_{DriveTr} = 0.94r^{2.00} + 0.01r^{2.50} + 0.05r^{2.88}$  |
| Tower                | 0.18  | $PF_{Tower} = r^{2.70}$  |
| Drivetrain + Nacelle | 0.54  | $PF_{N\&DT} = 0.85r^{2.00} + 0.01r^{2.50} + 0.04r^{2.60} + 0.04r^{2.88} + 0.08r^{3.00}$                              |
| Turbine DD           | 1.00  | $PF_{Turb} = 0.55r^{2.00} + 0.01r^{2.50} + 0.01r^{2.60} + 0.05r^{2.64} + 0.27r^{2.70} + 0.02r^{2.88} + 0.16r^{3.00}$ |

**Table 7.10 DD cost parametric factors**

Although the rotor and the tower are not affected directly with move from DFIG to DD, the removal of the gearbox disrupts subsystems shares of total costs and shares of each scaling exponent for all the subsystems. The move from DFIG to DD has the impact on scaling of reducing the exponents from 3 towards 2 as shown in Figure 7.16.

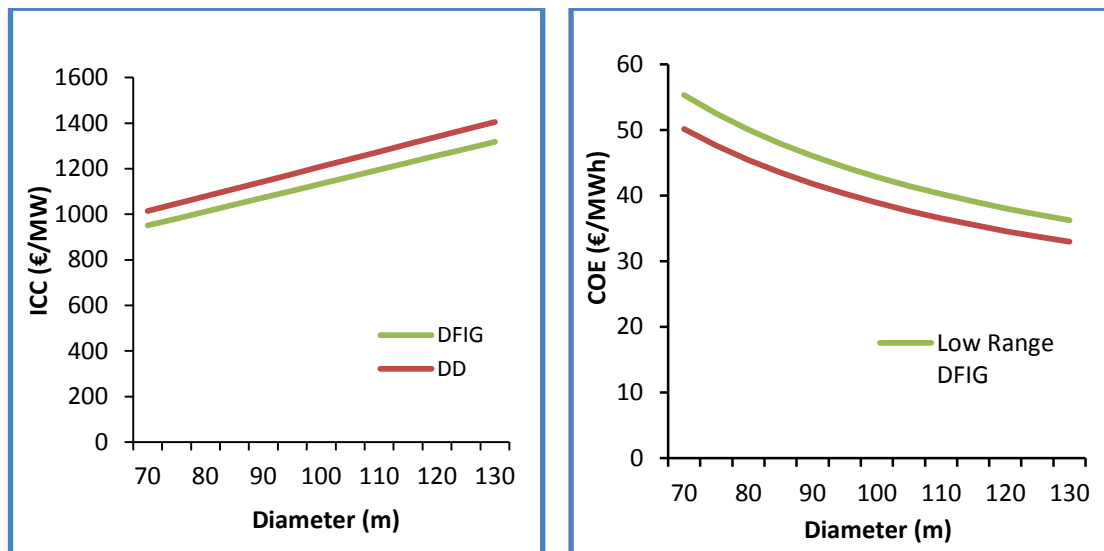


**Figure 7.16 Distribution of Scaling Exponents for DFIG turbine and DD turbines**

The DD has majority of the cost scaling with an exponent 2 giving it an advantage over DFIG for larger turbines. The realisation of ideal lower exponents for turbine

components requires continued evolution of the design and manufacturing processes for the components of the turbine. For example, new material for turbine blades would lower the exponents of the rotor which promises to have very high weight for large MW turbines.

Figure 7.17 gives the results for the capital costs ICC/MW on the left side and the COE on the right side.



**Figure 7.17 DD & DFIG ICC (left side) and Upscaling (right side) Results**

The normalised ICC as the turbine size for both cases increase as the turbine size increases at nearly the same rate with the DD capital costs higher than DFIG. The linear function shown in Figure 7.17 is due to the fact that the ICC scales with exponents between 2 and 3 whereas the rated power  $P$  used to normalise the ICC (the denominator) scale with a scaling exponent of 1.8. Theoretically the cost scales with an exponent of 3 and rated power scales by an exponent of 2 and the linear function scales linearly with  $D$  as the results show. However, as the turbine performance is taken into account, the trend for the two concepts differs as shown in the COE figure on the right. The DD COE reduces in both cases as the turbine size increases with the DD COE lower than the DFIG. This is due to the increased yield achieved by DD resulting from increased efficiency.

## 7.6 Discussion

The assessment of alternative concepts has improved relevancy when the COE is used as a metric of assessment. Innovations such as the move to larger turbines or large DD generators typically result in an increase in capital cost. However, when properly optimised, the improvements in performance result in reduced total costs of energy from the technology. A study carried out by BVG Associates on onshore wind turbines showed that a 10% reduction in capital costs typically results in a 7.5% reduction in COE and similar reduction in operational costs result in 2.5% reduction in COE. In contrast a 10% increase in annual energy production (AEP) result in a 10% reduction in COE (Valpy, 2013). Innovation improvements that result in significant increases in performance are more likely to be sustainable and compete with existing technology. Assessment methods such as the parametric models used in the study become important in providing quantitative evidence to stakeholders that although capital costs for a technology might be high, the increases in performance can counteract the negative impact of the capital costs. Upgradeable models such as these assist in the optimisation of parameters to ensure continued competitiveness.

The results of the parametric models are strongly dependent on component scaling exponents and shares. The components shares were derived from the reference turbine weight and cost. The scaling exponents used for both weight and cost scaling were derived from the detailed engineering based models used to estimate weight. The assumption for using these for cost was that cost varies linearly with weight. The impact of innovation however, can have a different effect on the two. Hendricks (2008) found that the scaling exponents for costs were less than the exponents for the mass for large offshore turbines.

The results of the parametric models for upscaling and for direct drive indicate changes in the wind energy costs when compared to the reference turbine. The cost results of the innovative drivetrain given in this chapter cannot be treated in isolation as they only explain possible cost trends due to changes introduced in the short term for some of the wind turbine models. Similarly, although upscaling has been gradual

over the years, the new larger turbines do not completely replace the smaller models but all exist together on the market.

The overall impact of innovation, whether radical or incremental, can be fully assessed if it is combined with other cost effecting factors. The level of establishment of the technology on the markets as well as other non-technological factors have an impact on the cost reduction potential of wind energy for both the DD and the DFIG concepts as the size increases. Moreover, the modelled results assume DD as a replacement which is not the case in reality. The drivetrain concepts co-exist with different market shares and the overall global cost of wind energy is a combination of turbines from different models or concepts. The DD concept was also introduced at a different point with the DFIG.

## 7.7 Conclusion

This chapter developed parametric based models for assessing the impact of change on the costs developed for the reference turbine in the previous chapters. The upscaling trend of wind turbines was modelled as an example of incremental change and the innovative direct drive (DD) drivetrain was modelled as an example of a radical change.

The weight results of the parametric models show good agreement with market data and the models can be used with a reasonable level of confidence. Upscaling increases turbine costs and ICC with power functions that are lower than the cubic function, but generally greater than 2. Normalised ICC scales with a near-linear function. The resulting COE indicate linear cost reduction trends as the turbines increase due to performance improvements. The DD COE is lower than the DFIG COE for the reference turbine and for upscaled turbines because of efficiency and reliability improvements resulting from the removal of the gearbox. The DD concept has significance for very large MW turbines because of potential continued cost reduction trends as the turbine size increases.

The impact of change is significant and is still anticipated, and therefore needs to be included or combined with other assessment methods that take into account other

factors in addition to scale and technological improvements. The usefulness of the modelled results is improved if they are put into context of current cost reduction trend analysis and forecasting methods such as the learning curve. The following chapter combines the results from the parametric model with learning curves analysis for improved assessment methods.



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## 8 Learning Curves and Engineering Assessments Integration Methods

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### 8.1 Introduction

Learning curves give an overall representation of long term historical costs and future cost predictions. Engineering assessments and parametric models used in this study illustrate that technological improvements have short to medium term impact on wind energy costs. The cost reduction potential through innovation is enhanced by a robust understanding of its impact on the whole cost system in the short, medium and long term. The combination of the proposed engineering based methods that isolate technology related drivers of cost with the learning curve analysis can provide a more holistic representation of cost developments that enables improved extrapolation of future costs for onshore wind technology. It is therefore necessary to analyse the level of impact on the cost of technology improvements in terms of upscaling and the direct drive drivetrain in the context of the whole cost reduction system. This chapter develops methods of improving learning curve analysis using the results of the engineering assessment of the reference turbine and the parametric modelling of upscaling trends and direct drive (DD) turbines.

Section 8.2 provides an overview of wind energy cost developments for capital costs (turbine costs and installed capacity costs (ICC)) and cost of energy (COE) together with the associated learning rates in the literature. Section 8.3 discusses methodological issues associated with improving learning curves using engineering based methods. The proposed methods for combining and integrating learning curves with engineering assessments methods are given in Section 8.4 and are applied to the onshore case study and the results are henceforth given. Section 8.5 discusses the developed methods and results and Section 8.6 concludes the chapter.

## 8.2 Onshore Wind Cost Developments and Learning Rates

Onshore wind energy displays clear cost reduction trends from the 1980s to present and in some geographical areas with good wind resource, wind energy is competitive with energy market prices (Wiser, Yang et al., 2011). Further analysis of historical wind energy costs trends shows a disruption to the cost reduction trend which indicates cost increases for a few years after costs hit their lowest levels around 2004 as discussed in earlier chapters. Although the cost reduction trend resume towards the end of the decade, the costs are yet to reduce to the historical low levels. However, both capital costs and cost of energy (COE) are expected to continue to reduce with experience coupled together with necessary technology advances expected for both onshore and offshore wind (Arwas, Charlesworth et al., 2012). Disruptions such as the cost increases in the 2000s are not predictable and other disruptions to the cost trends might occur again in the future.

### 8.2.1 Wind Energy Published Learning Rates

Unlike solar photovoltaics (PV) which has learning curves extrapolated from as early as 1960, significant learning curve time series for wind energy begin in the period 1980s to 1990s (Junginger, Van Sark et al., 2010). In Chapter 3 an average learning rate of 15% was given for onshore wind energy based on Junginger et al. (2010) and Figure 2.4 in Chapter 2. However, mainly due to differences in methodological approaches and choices of analysis variable parameters highlighted in Chapter 3, a wide range of published learning rates exist. For example, a study on global wind development by Nemet (2009) gave a learning rate of 11% for the period 1981 to 2004, however the learning rate varied significantly when other time periods were selected resulting in a learning rate range of between 3% and 17% being suggested (Green-X, 2012). The learning rates (LR) from major studies that review onshore wind energy learning rates were given in Table 3.4 in Section 3.

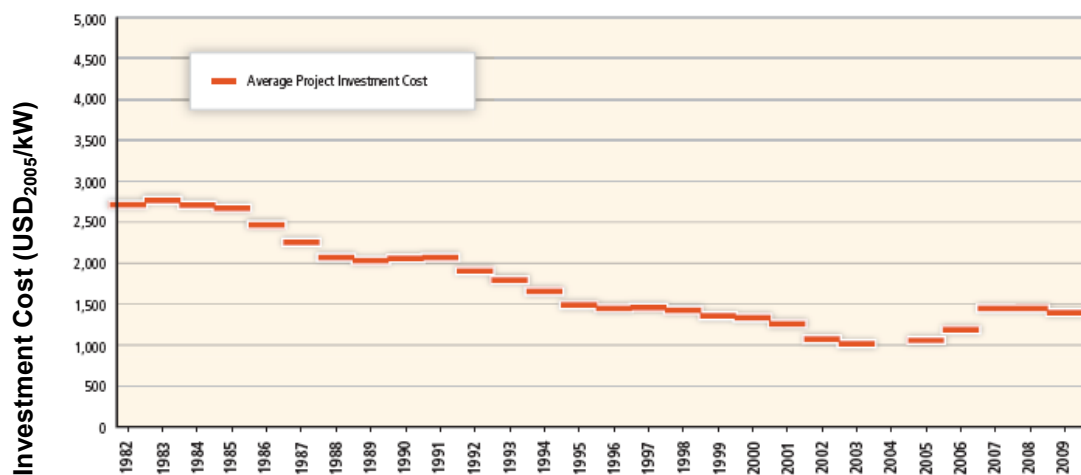
The majority of sources in Table 3.4 have learning rates based on learning curves for the time periods between 1980 and 2000 and the use of global cumulative capacity and more local data is common. Wise and Bolinger (2010) have data up to 2009 which is based on USA investment costs. It should also be noted that the majority of

learning curves are based on ICC and only 3 sources have learning rates for generation costs (COE based learning curves).

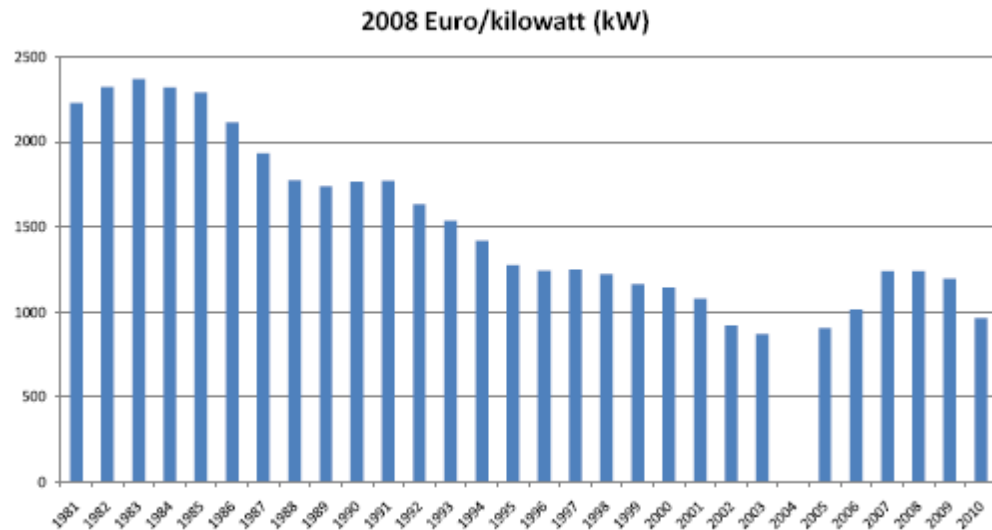
The COE based learning rates are generally higher than those for the ICC with the IEA (2000) study giving an extremely high learning rate of 32% for USA COE. The most possible explanation for the higher COE learning rates is because the capital cost reduction trends were coupled with annual electricity production (AEP) improvements and operation and maintenance (O&M) cost reductions. These are only reflected in the COE. Generally the learning rates for onshore wind given in Table 3.4 lie in the range 5% to 20% with possibilities of higher values for COE based learning.

### 8.2.2 Wind Energy Cost Developments

As demonstrated by wind energy learning curves, ICC and COE have reduced with time since the 1980s. Figure 8.1 and Figure 8.2 show ICC trends from the early 1980s for Denmark in \$/kW (Nielsen et al, 2010) and for global projects in €/kW (<http://gtms1314.wordpress.com>) respectively.



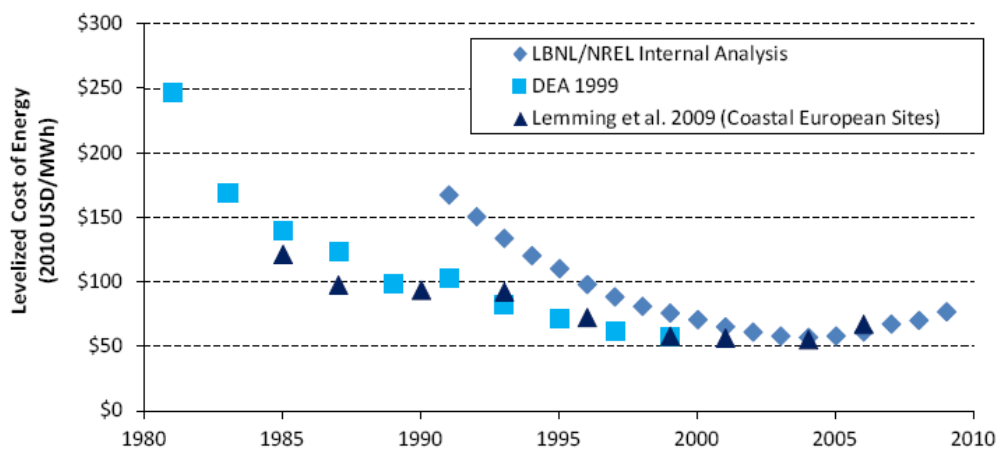
**Figure 8.1** ICC of onshore wind power plants in Denmark (IPCC, 2012)



**Figure 8.2** Global wind energy investment costs over the years. Source <http://gtms1314.wordpress.com> (Accessed February 2013)

From Figures 8.1<sup>6</sup> and 8.2, the ICC in €/kW can be estimated at around 2 400 €/kW in the early 1980s, reducing to about 1 700 €/kW in 1990 and about 1 000 €/kW in the 2000.

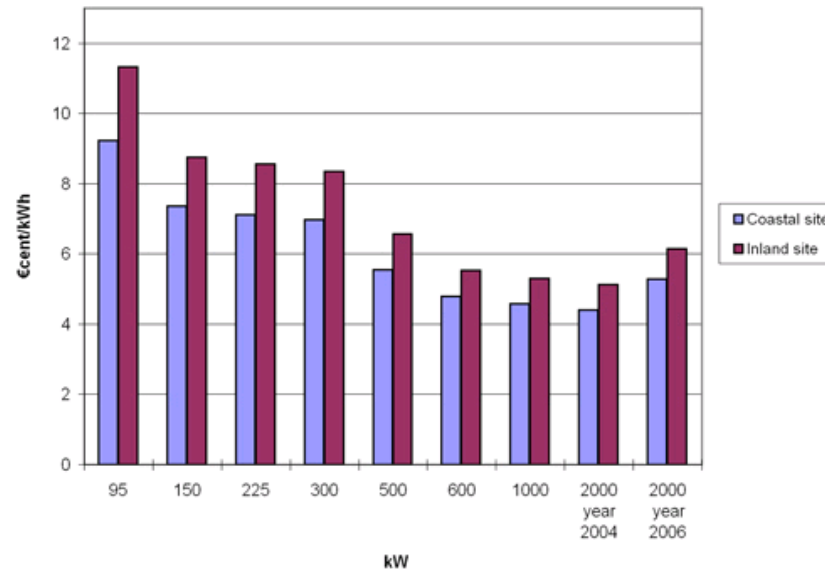
Figure 8.3 shows COE trends in the Us and Europe based on results from three studies (Lantz, Wiser et al., 2012).



**Figure 8.3** Estimated LCOE for wind energy for the US and Europe. (Lantz, Wiser et al., 2012)

<sup>6</sup> To convert US\$ to Euros (€). A currency conversion factor of \$1 to €0.8 is used as an average for 2005 figures and an index of 1.130 is used to account for inflation as discussed in Chapter 6.

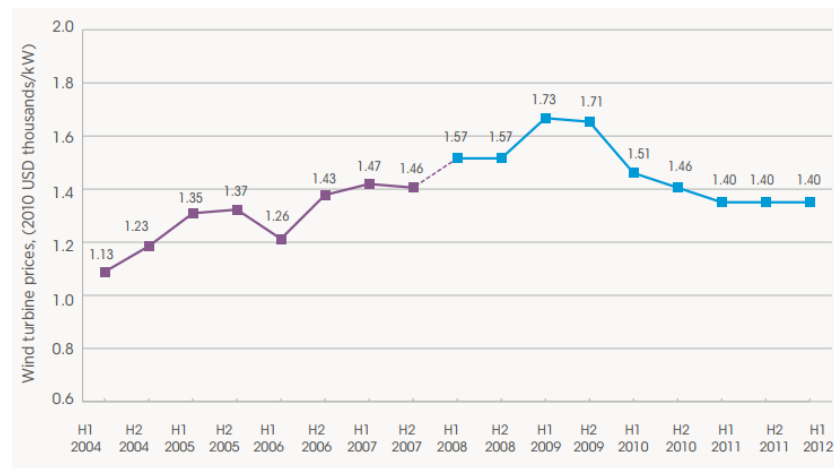
Figure 8.3 illustrate that the COE reduced from as high as 250 \$/MWh in the 1980s to nearly 50 \$/MWh in the early 2000s before sudden increases in the same manner as capital costs. Figure 8.4 shows the trend COE in ¢cents/kWh from 1980 for a 95 kW turbine to 2006 for a 2 MW turbine (Morthorst, Auer et al., 2009).



**Figure 8.4 COE trends for onshore and offshore wind turbines.**

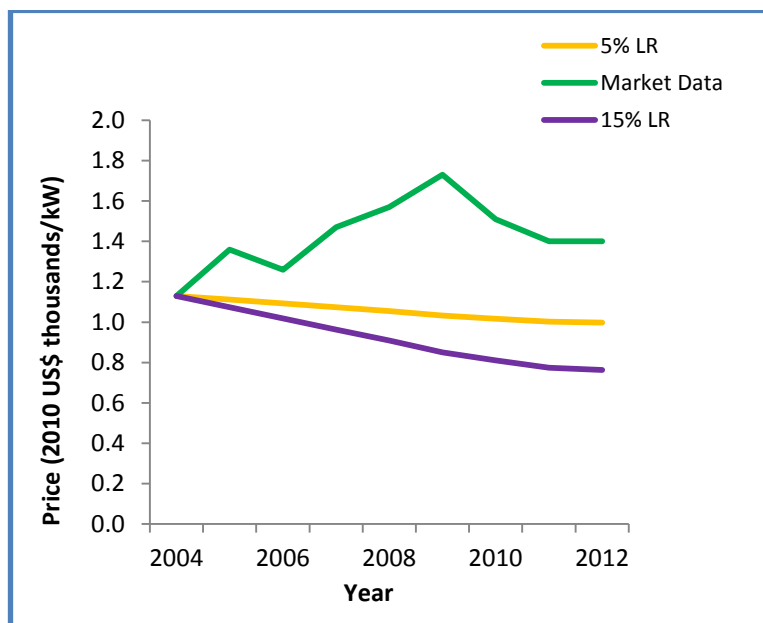
The overall trend for the ICC/kW and the COE show similar cost reduction trends with a dip in the early to mid 2000s. It can be observed from Figures 8.3 and 8.4 that in the early years, 1980s to 1990s, steeper COE cost reduction trends were observed compared to ICC trends in Figures 8.1 and 8.2. The COE in Figure 8.3 shows a 60% cost reduction for the 1980 to 1990 compared to the ICC 30% cost reduction from Figures 8.1 and 8.2.

Historical learning curves predict continuous cost reduction with increasing capacity. There is no apparent evidence that disruption in wind energy cost reduction trends due to capital cost increases in the 2000s, which was not just limited to onshore wind but nearly all technologies (Greenacre, Gross et al., 2010; Junginger, Van Sark et al., 2010), has been modelled in classical learning curves. Figure 8.5 shows the turbine cost trends for wind energy as represented by turbine prices from 2004 to 2012.



**Figure 8.5** Wind turbine Prices in 1 000\$/kW (<http://gtms1303.wordpress.com>, Accessed 1 March 2013)

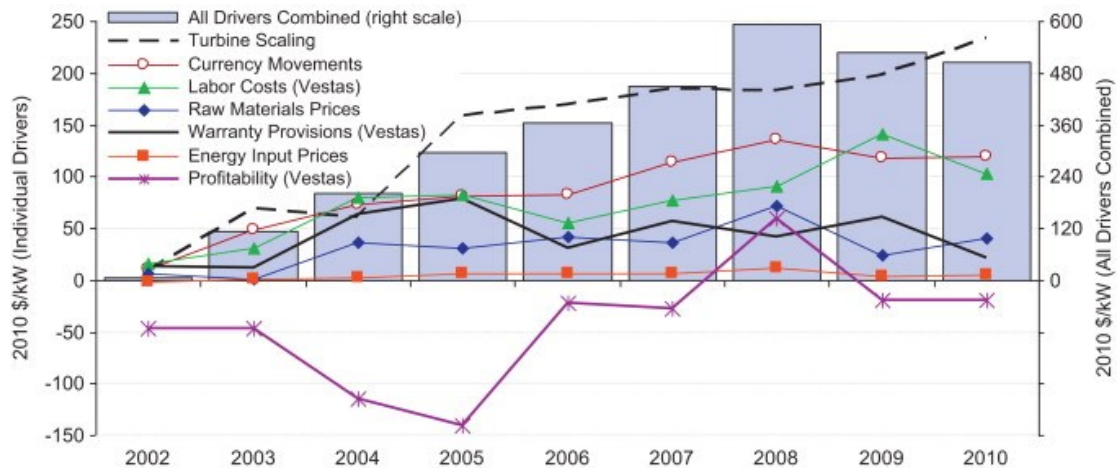
Figure 8.5 illustrates the impact of the capital cost increases in the 2000s on turbine prices. At its peak in 2009, the price of the turbine had increased by 53% from the low 2006 levels whereas 2012 levels indicate that the price had only reduced by 19% from the 2009 levels. Figure 8.6 shows the turbine price trend in Figure 8.5 with annual costs averaged from the first half (H1) and second half (H2) costs given in Figure 8.5, compared with hypothetical learning curves with 5% and 15% learning rates based on the 2004 turbine price levels.



**Figure 8.6** Turbine prices and learning curves (Market data based on Figure 8.5)

Although the learning rates published in the literature can be used to describe historical costs from the 1980s or 1990s to the early 2000s, extrapolations beyond the mid 2000s using simple learning curves needs to be treated with caution. Further analysis of other possible sources of cost reduction or cost increases such as the case in the mid 2000s has the potential of improving the quality and credibility of learning curves.

Bolinger and Wiser (2012) isolated 7 endogenous and exogenous factors that affected the cost and price of wind turbines during the period of cost and price increases in the 2000s and the upscaling of wind turbines was found to be one of the endogenous cost drivers. Figure 8.2 gives the results of their study and shows upscaling (dotted line) as the source which had the highest impact of increasing turbine costs and prices over the period.



**Figure 8.7** Wind turbine cost drivers (Bolinger and Wiser, 2012)

Modelling the impact of upscaling can be a first step towards the development of quantitative methods for assessing the cumulative impact of cost drivers such as those in Figure 8.7. In simplified models, given such cost trends data as in Figure 8.7, the impact of other factors such as raw material price increases can be compared relative to the upscaling model results from the parametric model.

The methodological issues associated with the development of generic methods for improving learning curve analysis to include such factors as the cost impact of upscaling are discussed below.

### 8.3 Learning Curve Analysis Improvements

The assessment of the impact of scaling on wind energy costs stand to be more beneficial when combined together with learning curves (Bolinger and Wiser, 2011). Hendricks (2008) emphasised the need for further analysis to enhance engineering based upscaling models through the identification of the learning curve contribution in the data trends. As discussed in Chapter 3, there are challenges in the combination of learning curves and detailed engineering assessments. The parametric modelling used in this study provides means of projecting data from the detailed engineering assessments so as to account for several turbines with different sizes in learning curves analyses. The parametric model simplifies the projection of cost data for a new turbine from the reference costs through the use parametric factor that has only diameter  $D$  as the variable factor thus allowing the exploration of different turbines.

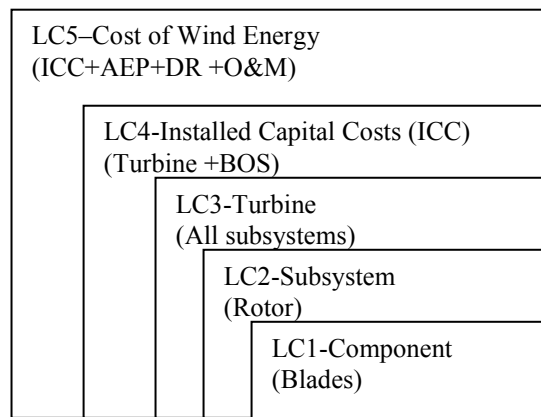
#### 8.3.1 Disaggregation of Learning Curves

In Chapter 2 it was discussed that the main limitations and caveats in the use of the learning curve analysis are due to their aggregate nature. Attempts to separate learning curves can reveal factors that are hidden in the learning curve leading to an enhanced understanding of the drivers of cost and their impact on overall wind energy costs. It should be recognised that wind energy is an aggregate technological system with several elements, and the representation of overall costs cover a number of cost factors some of which might be overshadowed or left out in the representation.

The main cost centre for wind energy, the wind turbine, is made up of components with different cost drivers. It would be worth developing learning curves for each of the major components such as the blades and the hub. Alternatively, to reduce modelling effort for the components, subsystem based learning curves for the rotor, the drivetrain with the nacelle and the tower might be more valuable. Subsystem



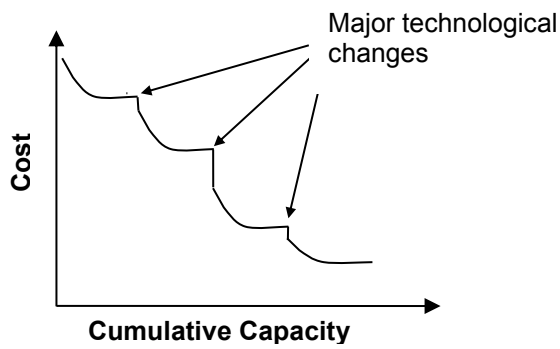
level analysis can provide more generic analyses compared to specific components which might exhibit major differences for manufacturers. This approach might help in identifying not only areas where innovation is needed most, but also where there is an overall positive impact on cost reduction. Figure 8.8 illustrates possible categorisation of learning curves for wind energy.



**Figure 8.8** Component based disaggregated learning curves (LC)

This study will focus on the more aggregated learning curves LC4 and LC5 in the first instance which take into account which are typical with the learning curves available in literature as given in Table 3.4 (ICC and COE learning curves).

Disaggregation of wind energy learning curves can take another form, wherein curves are disaggregated into smaller timeframes linked to onshore wind technological trends. Major radical changes or cumulative impact of incremental changes with significant cost reduction potentials might call for construction of new learning curves or reconstruction of the aggregated learning curve at strategic historical points in time. For example, the introduction of variable speed in the early 1990s might necessitate the construction of new curves from that period of time, which are different from those assumed from 1980. The new learning curve might have either a new learning rate (LR) or a new start point unit cost ( $C_0$ ) or both. Figure 8.9 is a representation of possible resulting family of learning curves.

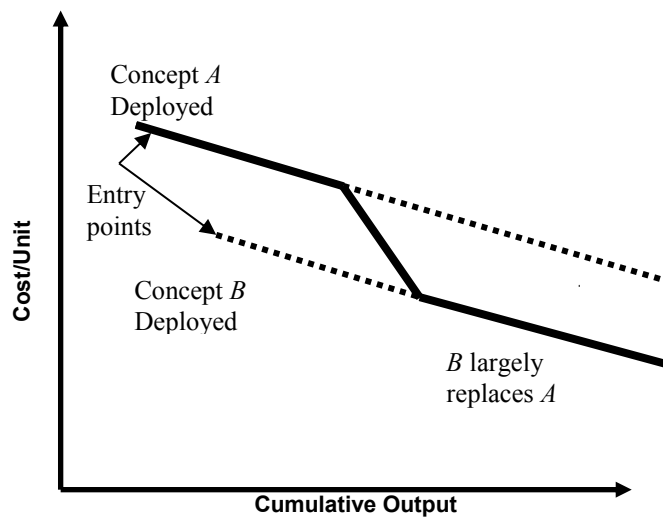


**Figure 8.9** Illustration of possible Innovation Based Learning Curves

Disaggregation or separation of learning curves has the capability to capture the impact of other technical cost drivers in addition to upscaling and drivetrain changes such as the move from glass fibre blades to carbon composite blades. Further development can lead to the inclusion of non technical factors that could have an impact on the cost of a technology. The disaggregation of learning curves is achieved through qualitative and quantitative engineering based assessments at strategic points according to the technology's development trends. For example, the sudden cost increases that affected the majority of energy supply technologies in the 2000s, mainly due to increased demand and raw materials price increases can be captured by assessing overall costs taking into account this development for the years between 2004 and 2009.

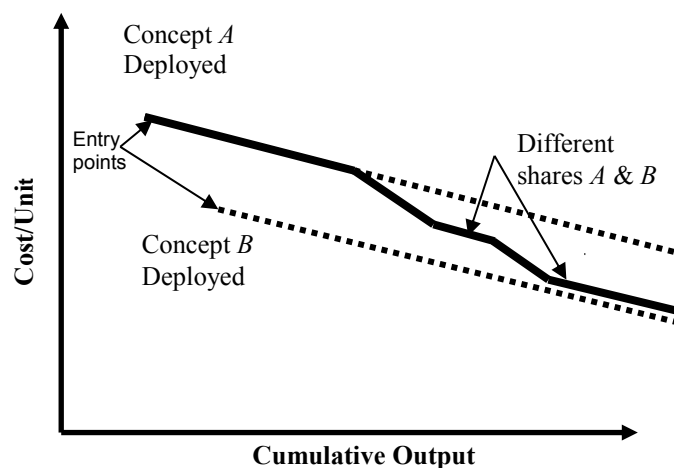
### 8.3.2 Learning Curves and Technological Improvements

When a concept  $B$  enters the market following technological improvements of the existing concept  $A$ , there is a possible transition in the learning curves as the newer technology settles on the market as illustrated in Figure 8.10.



**Figure 8.10** Hypothetical behaviour of a replacing alternative concept. Adapted from (IEA, 2000)

This is typical for radical changes and an example is the move from fixed speed to variable speed turbines where very few if any fixed speed turbines exist on the market for MW turbines. However, in most cases the alternative concept *B* does not completely replace *A*, but the two concepts will co-exist with different shares in a technology mix that is favourable in terms of cost and performance. The resulting learning curves will depend on the cost developments of the two technology concepts as illustrated in Figure 8.11.



**Figure 8.11** Hypothetical behaviour of alternative technology concepts coexisting. Adapted from (IEA, 2000)

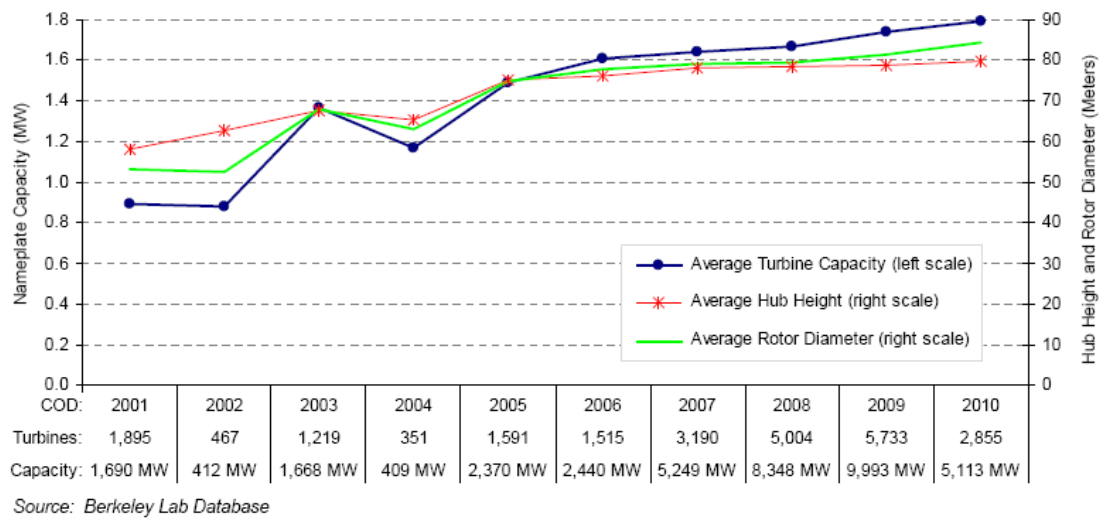
Figure 8.11 is based on the assumption that *B* is cheaper but in reality it might be more expensive especially in the early days as discussed in Chapter 3. However, the costs of *B* will likely stabilise in an improved way than the more established *A* it learns from. As an improvement of *A*, *B* will have more cost advantages than the earlier concept hence its deployment. *B* might also be more expensive in terms of capital costs, but more beneficial in the annual energy production though improved performance. In such a case the anticipated cost reduction trend can only be realised for COE based assessments rather than investment costs.

In some cases more than 2 variations of the technology can be on the market. The MW turbines on the market globally vary from the 1 to 1.5 MW turbine range to the large 6-7.5 MW range mainly for offshore applications. Different market shares of the direct drive and DFIG have existed on the market since the 1990s.

### **8.3.2.1 Upscaling Market Share Trends**

The upscaling of MW turbines has not resulted in the complete replacement of smaller turbines, but rather they coexist on the market. Moreover, installed turbines will remain until the end of their lifetime of 20 to 25 years where they will be more likely to be replaced by larger and improved alternatives. It is assumed that for incremental upscaling change, the newer turbines with larger capacity will dominate the market and influence the average global costs.

The parametric modelling cost results for each diameter imply the existence of a sole turbine design model on the market. The global installed capacity is a mixture of turbines of different sizes and it will be more appropriate to use the average turbine diameters to represent turbine growth. Historical data on turbine growth based on average turbine size trends is more limited than data on the largest wind turbines on the market shown in Figures 4.9 and 4.10. Figure 8.12 shows the trends for the average size US turbines on the market between the year 2001 and 2010.

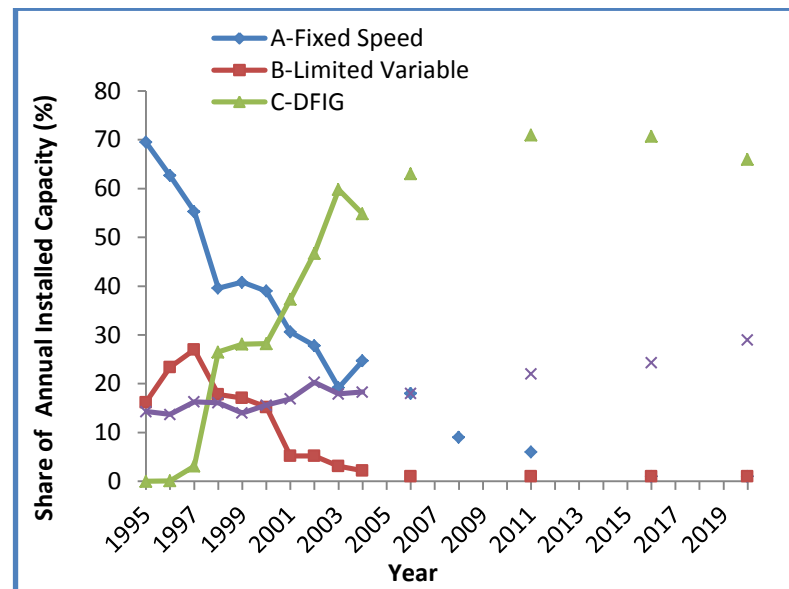


**Figure 8.12 Turbine Average Sizes(Bolinger and Wiser, 2012)**

The cost assessment methods in this study will be based on the representation of an average market with a mixture of turbines based on data both the largest turbines on the market from 1990 and the average data for comparison purposes from the US data from 2001. An average market is assumed based on a combination of shares of low cost and high cost turbines based on the reference DFIG turbine as well as the DD turbine to account for possible differences in sizes.

### 8.3.2.2 Drivetrain Market Share Trends Projection

The direct drive turbine concept has always maintained a share of the market that has largely been influenced by Enercon's electrical excited drive synchronous generator DDSG (or WRSB) share of the market. In recent years however, other players have started to manufacture DD with some with more innovative concepts such as the permanent magnet synchronous generator (PMSG), thus increasing the overall market share of DD. The trend of the DD concepts on the market can be obtained by extrapolating data from Hansen and Hansen (2007) for 1995 to 2005 discussed in Chapter 4 where four types of drivetrain systems (Types A to D) were defined, by incorporating data on DD shares from more recent studies (Globaldata, 2012; TMR, 2013). It was assumed that the two concepts DFIG and the direct drive DD (Type C and D from Figure 4.13) have the majority market share. The resulting extrapolation of Figure 4.13 based on Hansen and Hansen (2007) is shown in Figure 8.13.



**Figure 8.13 Drivetrain Concepts Projected Trends. Adapted from (Hansen and Hansen, 2007).**

Table 8.1 gives the assumption for the estimations of detailed drivetrain market shares.

| Year | (DD) Market share % | Assumptions  |
|------|---------------------|--|
| 2006 | 18                  | Type C and D make up 90% (B and A still significant at 10%)                                |
| 2010 | 17.4                | C and D make up 95% of the market as the B and C further reduce significance on the market |
| 2011 | 22                  | C and D, 95%. Other concepts make up the 5%  |
| 2016 | 24.3                | C and D 90%. Innovative concepts such as medium speed drivetrain increase share            |
| 2020 | 29                  | C and D, 85%   |

**Table 8.1 Drivetrain projected market share trends. (Hansen and Hansen, 2007). DD market share data from (Globaldata, 2012; TMR, 2013).**

To simplify the analyses for this study, it is assumed that the average share of DD is 15% from 1990 to 2005 and 20% thereafter to 2012. Higher shares of DD will be needed for projections beyond 2012 such as those in Table 8.1 for 2016 and 2020.

## 8.4 Proposed Improved Learning Curve Methods

### 8.4.1 Simple Learning Curves

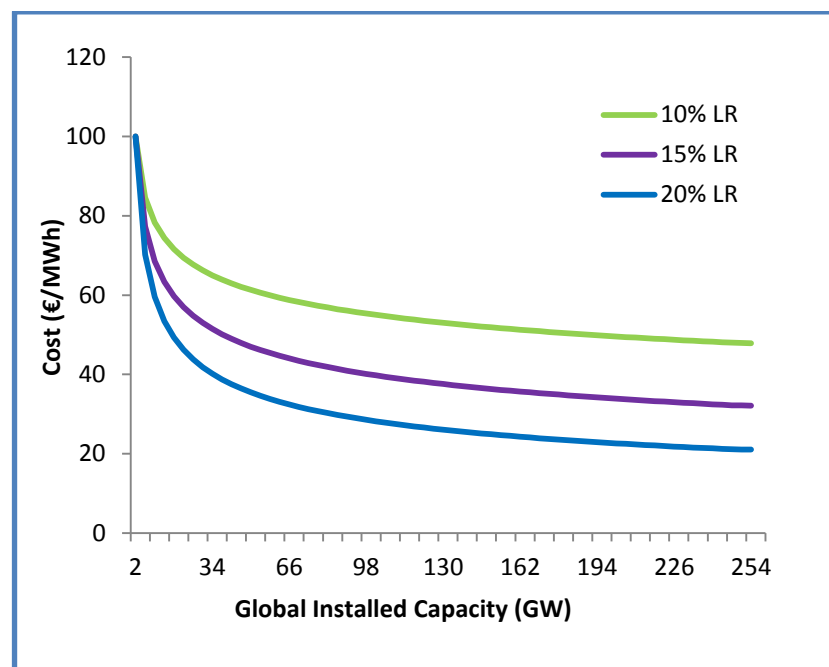
The development of simple learning curves involves a choice of parameters and variables discussed in section 3.2. In terms of geographical boundaries, global cumulative installed capacity is used to represent experience. This is based on the assumption that the cost of wind energy whether at local or global level is sensitive to global installed capacity due to the globalisation of wind market. Although the majority of learning rates are based on investment costs, the benefits of innovation might not be realised in the form of capital cost reduction but in improvements in turbine performance or operation and maintenance (O&M) costs as was the case for direct drive model results in the Chapter 7. It is therefore necessary to model learning curves based on overall generation costs in the form of cost of energy (COE) in €/MWh. Learning curves for the ICC normalised by the turbine capacity in €/MW are also considered for comparison purposes.

The start point for the learning analysis is set at 1990 and the global cumulative capacity for that year is considered as the first unit. This year is chosen taking into consideration the timings of the upscaling trend of MW turbines and the introduction of direct drive turbines. Simple learning curves with learning rates in the range 10% to 20% were plotted using a representative COE of 150 €/MWh for 1980 reducing to around 100 €/MWh for 1990 derived from Figures 8.3 and 8.4 and EWEA studies (Morthorst, Auer et al., 2009; EWEA, 2010; EWEA, 2012). Table 8.2 summarises the parameters used to develop the simple learning curves to be improved by engineering based methods.

| Variable                         | Value     |
|----------------------------------|-----------|
| Learning rates, %                | 10-20     |
| Timeframe                        | 1990-2010 |
| COE first unit, $C_0$ , €/MWh    | 10        |
| Cumulative installation 1990, GW | 1.93      |
| Cumulative installation 2012, GW | 254       |

**Table 8.2      Learning curves variable parameters**

Figure 8.14 shows the resulting simple learning curves.



**Figure 8.14** Wind energy simple learning curves based on Equation 2.1 and Figure 4.1

The combination of engineering assessment and learning curve method is proposed in two stages. Initially, the results from the parametric model are used in a complementary way for a better understanding of cost trends behaviour in the short term by plotting upscaling results on the same chart as the learning curves. In the second stage the engineering and parametric based models results are integrated in a way that alters the learning curve by introducing new learning curve start points and/or new learning rates. Both methods of learning curve analysis improvements are described below.

#### 8.4.2 Complementary Analysis

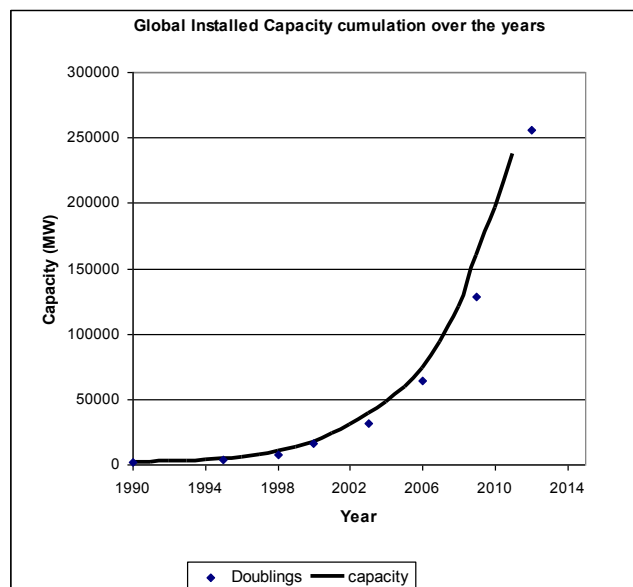
The first approach involves plotting together historical learning curves and parametrically modelled results of alternative technology concepts so as to analyse the fit of the plots and observe any apparent shifts or step changes in the learning curves. The main challenge is in the plotting of learning curve cost trends whose independent variable is cumulative installed capacity on the same plot with the



parametric modelling upscaling costs trends whose independent variable is not cumulative capacity, but turbine diameter. The trends of the global cumulative capacity and that of the turbine size trends from 1990 to 2012 provide a link for learning curves analysis.

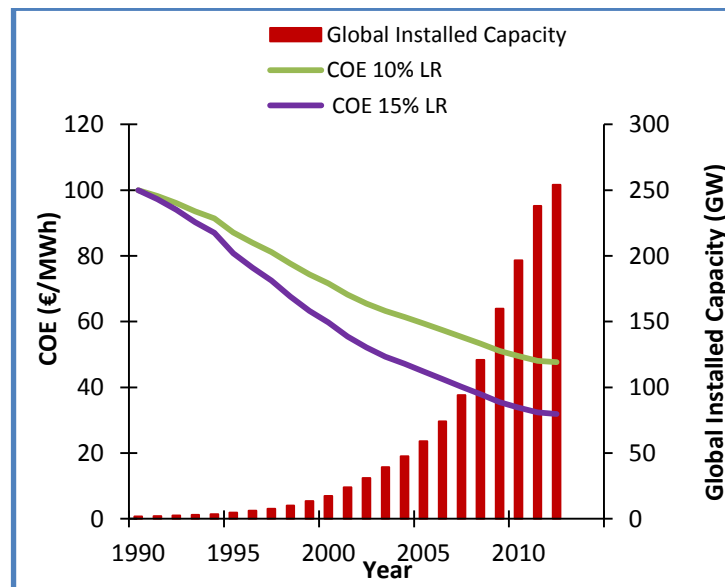
The following steps describe the approach used to combine learning curves and engineering assessment and parametric results for this study:

- i. Global cumulative installed capacity trends of onshore wind were analysed and plotted for the period (WWEA, 2011; GWEC, 2012) as shown in Figure 8.15 which also illustrates capacity doubling trends.



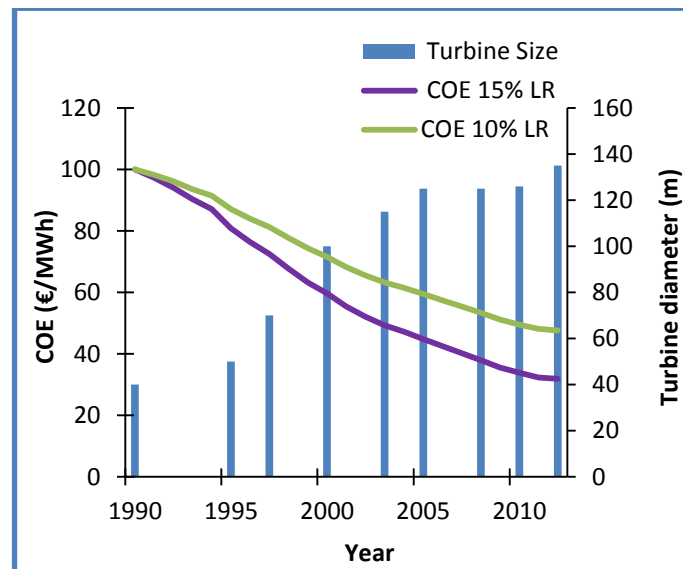
**Figure 8.15 Global Cumulative Onshore Wind Installed Capacity and Capacity Doublings**

- ii. Using data from Table 8.2 and equation 2.1, learning curves were plotted using the annual cumulative capacity values for each year. The installed cumulative capacity was replaced as the independent variable on the learning curve by the year the global capacity was achieved. Figure 8.16 shows plots of learning curves for each year.



**Figure 8.16 Learning Effects and Annual Cumulative Onshore Wind Installed Capacity**

- iii. Turbine growth trends from 1990 to 2012 were analysed and the size represented by the diameter for each of the years with available relevant data was plotted. Initially the size growth for the largest turbine based on Figures 4.9 and 4.10 and was used. The turbine growth trend for the period was superimposed onto the learning curves plots in Figure 8.16 as shown as shown in Figure 8.17.



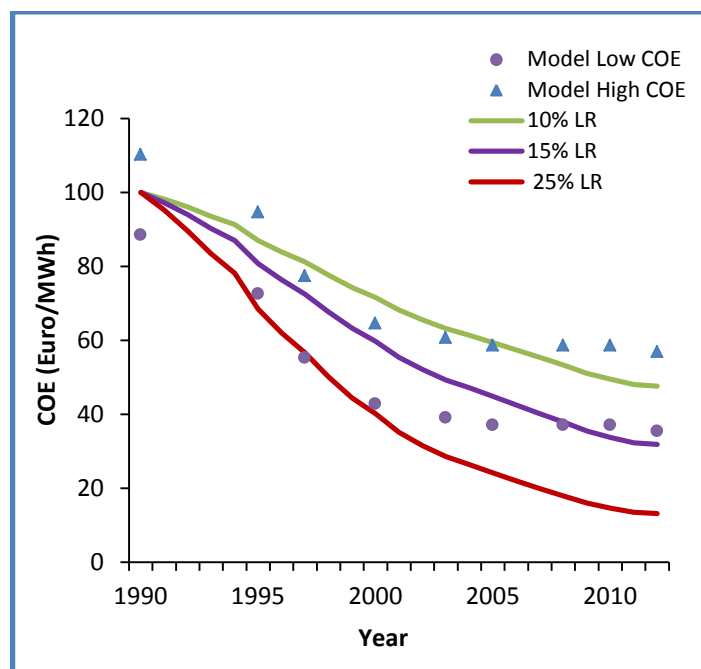
**Figure 8.17 Learning effects and annual turbine size (diameter) growth for commercial turbines**

- iv. Costs for turbines were then estimated for each of the diameters in Figure 8.17 using cost estimation relationships (CERs) from the developed parametric models. These costs were then plotted for each of the years together with the learning curves.

For example, for the year 2005, from Figure 8.17 the global cumulative capacity of 59.1 GW was used for plotting learning curves points for that year in the same figure. The turbine diameter of 115m for the year 2005 is used in the CERs with  $r = 115/80$  ( $D = 115\text{m}$  and  $D_{ref} = 80\text{ m}$ ) to find ICC and COE that relate to that size. These are then plotted on the plot with the learning curves. The drivetrain trends and drivetrain costs from the parametric model were also used to plot drivetrain related costs for the period 1990 to 2012 together with learning.

### 8.4.3 Complementary Analysis Results

The costs of a 2 MW reference turbine with a double fed induction generator (DFIG) were estimated in a range based on a high and a low level cost scenarios in Chapter 6 and these were projected upscaled turbines using the parametric model. The resulting plots were compared to the family of learning curves and the fit of the plot was analysed shown in Figure 8.18.

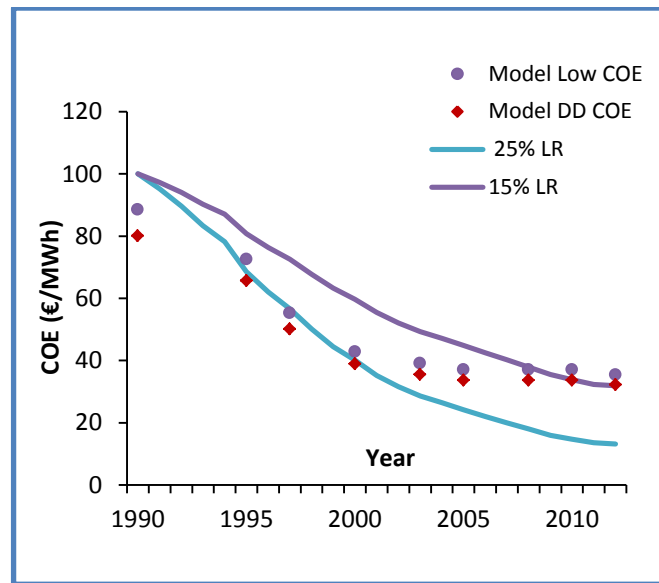


**Figure 8.18 Complementary Learning and Effects, DFIG COE Results**

The upscaling Figure 8.18 is plot for the low and high COE results for each point with a different turbine diameter according to the size growth trends. The low range COE upscaling results trend lie between the 15% LR and the 25% LR. The rapid change in the largest diameter between 1995 and 2000 translate to the higher learning rate of 25%. From around 2003 there is a stepping up shift towards the lower learning rate curve of 15%. This is due to the levelling out of the turbine large diameter  $D$  demonstrated in Figure 7.1 because of challenges associated with continued upscaling of onshore turbines. The high COE upscaling results lie between 15% LR and 20% LR and behave in the same way.

The DD COE upscaling results (Figure 8.19) also behave in the same way as the reference DFIG turbine plotted (Figure 8.18), with cost slightly lower for each diameter. This means that the same rate of cost reduction as the diameter increases. The scaling exponents that were used for the DD concept were similar to those of the DFIG reference turbine. Further analysis of the changes in the DD concept

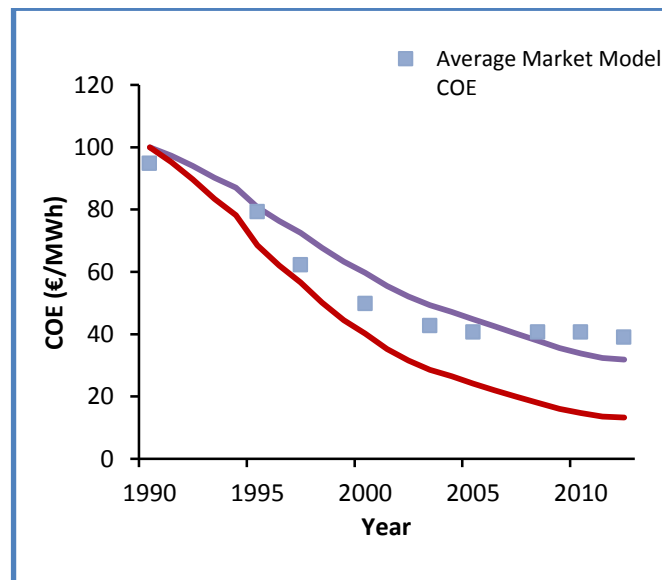
components might result in improved scaling exponents, more relevant to the upscaling of DD turbines.



**Figure 8.19 Complementary Learning and Effects, DD COE Results**

To model an average market the following market mixes are considered:

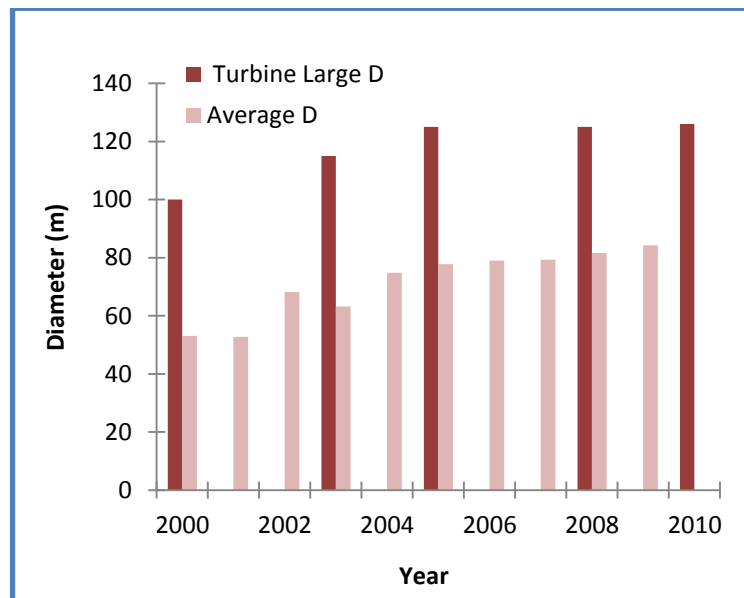
- 1) 1990-1995: 15% DD, 50% low cost turbines and 35% high cost turbines
- 2) 1995–2010: 20% DD, 60% low cost turbines and 20% high cost turbines.



**Figure 8.20** Learning and Upscaling Effects on COE for an Average Market

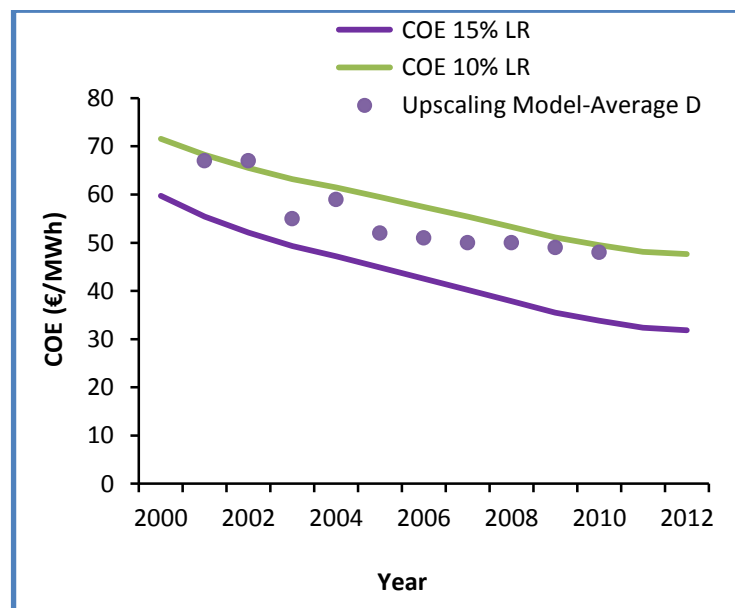
The COE results for the average market lie between 15% and 20% learning rate range, and this is sensitive to the market shares assumptions. Fast turbine size growth rates as in the early 1990s imply higher learning rates and shifts towards curves with higher learning rates.

The modelled results given so far are based on size growth defined by the largest turbine on the market. There are marked differences between the largest turbines on the market over the years and the average as shown in Figure 8.21 which plots the average turbine sizes for US turbines for the years 2000 to 2010 together with the largest turbine sizes.



**Figure 8.21 Turbine Growth- Large Turbine and Average Turbine Size**

The average turbine size trend in Figure 8.21 does not show as much growth as the largest turbine on the market. Figure 8.22 plots upscaling modelling results for the average size turbine for each year.



**Figure 8.22 Learning and Upscaling Effects on COE based on Average Diameter**

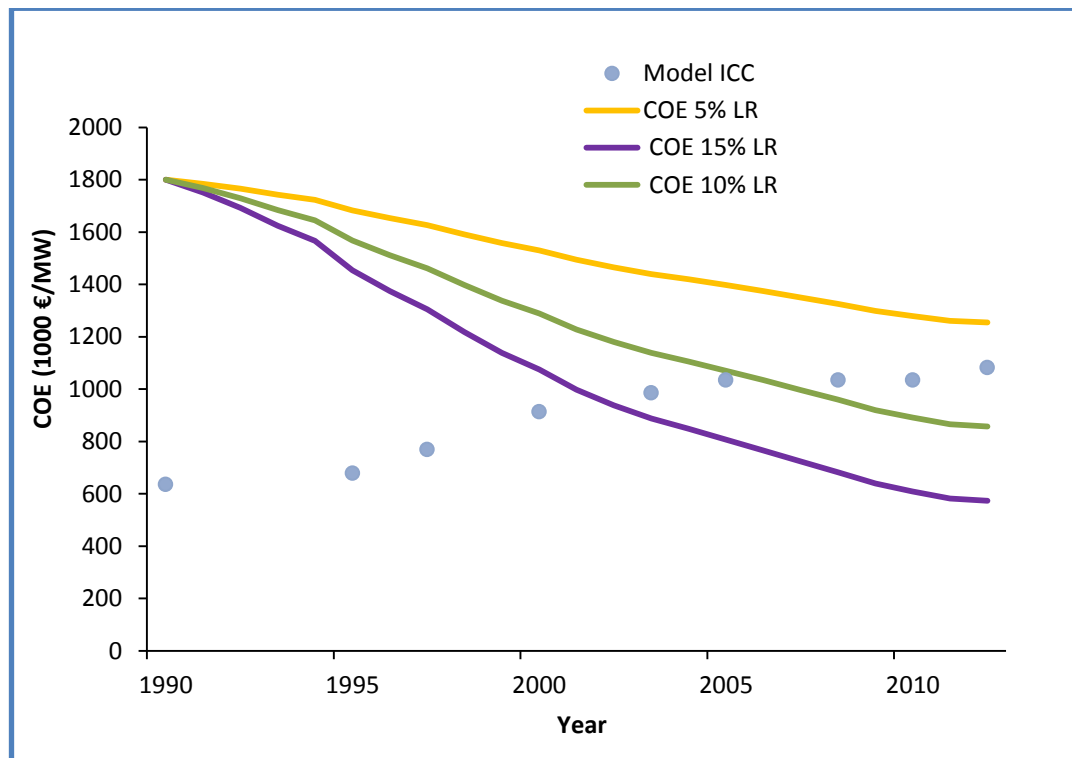
Costs lie between 10% and 15% showing a flattening trend towards the 10% LR curve because of the flattening of the turbine size from the 2000s. It would be worth

analysing the trend within the context of global average turbine size data that is pre-2000. The use of the average turbine size requires some caution as differences might exist in defining the average turbine size. The average might be estimated using the number of turbines which would result in average turbine sizes biased towards smaller turbines which are greater in numbers compared to the larger turbines with large rated capacities. The average turbine sizes also vary for different countries because of different wind regimes and differences in projects and this poses a challenge when using average size global data.

Generally, when plotted with learning curves, the upscaling results over 20 years from 1990 lie within the range of learning rates in literature between 10% and 25% with higher rates in the 1990s. Consequently, the upscaling results for the first half of the 20 years up to 2000 lie on higher learning rate curves than the second half. This is because of the rapid growth in the turbine size up to the 2000s. Continued rapid growth might have implied continued higher rates of cost reduction. The flattening of the turbine size trend in the 2000s, due to design challenges associated with very large turbines such as increased blade weight, has the impact of having the cost trend step up to curves with lower LR. On the other hand, the move to larger turbines or the increase in shares of large turbines on the market will have a step down effect to curves of higher learning rates.

The results above are all based on generation costs or COE. Figure 8.23 gives the results for capital costs modelled as the installed capital costs (ICC/MW).

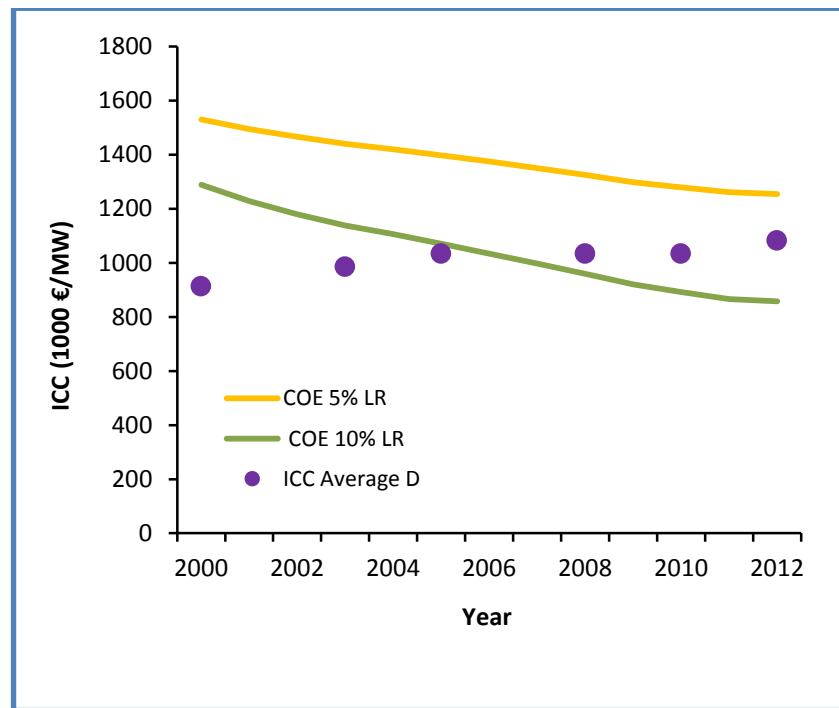




**Figure 8.23** Learning and Upscaling Effects on ICC for Large Diameter Size

Capital costs (turbine or ICC) increase as the turbine size increases as discussed in Chapter 7. As can be seen from Figure 8.25, it is difficult to plot normalised ICC with learning curves because on one hand the overall costs reduce with time due to experience whereas for scaling, capital costs increase with turbine size  $D$ . Theoretically the capital costs scale with a cubic function and the rated power used to normalise the capital costs vary with a square function. The result is a linear function. Although lower scaling exponents were obtained using the parametric model, the ICC still increase with  $D$  or with time.

Figure 8.24 shows the ICC plot of the upscaling model for the average market based on shares of low cost, high cost and DD turbines defined earlier.



**Figure 8.24 Learning and Upscaling Effects on ICC for Average Diameter**

It can be observed from Figure 8.24 that plotting average turbine size upscaling ICC with learning curves results in an improved fit but the size data for the second half of the period under study and is based on US turbines. This still shows a contradicting cost increase trend similar to that observed by Bolinger and Wiser (2011). The upscaling model is therefore not ideal for plotting with learning curves because the former predicts cost reduction whereas the latter imply capital cost increases. This study will therefore focus on the use of COE for developing integration methods. However, the use of COE for generic methods is associated with challenges due to COE sensitivity to project specific factors. The study will maintain the aim of developing improved methods of assessing technological change rather than developing absolute values which are achievable with improved data methods.

It can be observed from the Figure 8.24 that ICC learning curves have lower learning rates than COE learning curves. Capacity factors have improved with time as the turbine size upscaled (Lantz and Hand) and the impact is not captured in the ICC but in the COE.

Although the engineering assessment results of the upscaling models for the DFIG 2 MW reference turbine and the DD turbine given in this subsection lie within the ranges of existing learning curves, the ranges are however, wide. What can be observed from this approach are indications that where learning curves have been used to represent cost reductions using a single learning rate, disruptions in the costs are observed in the short to medium term with instances of up-stepping and down-stepping between learning curves. With this evidence, it would be more beneficial to develop methods in which the learning curve itself can be improved by the inclusion of data from the engineering assessments and parametric model. This integration method is given below.

#### **8.4.4 Integration Analysis**

The integration of engineering assessment models leads to the alteration of the learning curves by factoring-in the results from the engineering assessments into the learning curve equation. This involves consideration of historical points where the impact of scaling or drivetrain was significant. It is assumed that at these points the learning curve is altered due to changes in the costs or cost reduction potential marking the beginning of a different curve at that point. The cost data for constructing the new learning curve at that point is obtained by estimating the average cost of the design concepts on the market. Further qualitative assessments identify cost reduction potential rates for specific time periods, which might imply different learning rates compared to previous ones. New learning curves are obtained for each position and the cost trend is assumed to shift to the new curve until another significant technological change. For scaling, this means significant diameter change for turbines on the market

In a previous study, an improved fit of turbine price was obtained using a model based on the combination of learning curves and engineering based scaling model compared to plots on simple learning curve (Coulomb and Neuhoﬀ, 2006). The integration methods outlined above upgrade the learning curve equation 8.1 for estimating cost at point in time  $C_t$ .

$$C_t = C_0 q_t^{-b} \quad 8.1$$

Where  $C_0$  is the cost of the first unit, and  $b$  is experience index used to estimate the learning rate. It is assumed that over time either the value of  $C_0$  and/or  $b$  change depending on detailed analysis of the trends for each year. This results in a series of learning curves each applying for a period till the transition to another, due to a significant change in cost at the next strategic point in time. Engineering assessments and parametric modelling cost methods are used to determine the most relevant cost estimate for the first unit at each point. The results of the scaling model are used to develop such curves as described below.

Knowing the diameter  $D_0$  of the turbine for the year of the first unit, the scaling model can be defined using Equations 7.9 and 7.11 as:

$$C_0 = C_{ref} PF_0 \quad 8.2$$

Where  $C_{ref}$  is the reference turbine cost estimated using the Sunderland based engineering assessment model and  $PF_0$  is the parametric factor in terms of  $r$  ( $r = D/D_{ref}$ ) developed in Chapter 7 and used to project the cost for the first unit for the learning curve analysis from the reference model costs estimated in Chapter 6. Combining the learning curve model Equation 8.1 with scaling models Equations 7.1 and 7.11, the integrated model becomes:

$$C_t = (C_{ref} PF_0) q_t^{-b} \quad 8.2$$

The choice of the most relevant learning rates or values for  $b$  for Equation 8.3 at each strategic point in time is supported by a combination of qualitative and quantitative methods. The complementary plots given in Figures 8.18 to 8.20 provide a guide as to the range of learning rates for different periods and expert judgements are required in the analysis of historical trends and cost reduction potential to support these learning rates estimates.

The COE learning rates from relevant studies in Table 3.4 vary from 17% to 32% for the period between 1980 and 2000. There is limited data on COE learning rates in

literature beyond 2002. ICC learning rates for periods up to 2000 vary between 5% and 19% and learning rates projected to 2004 and 2009 are 11% and 9% respectively. Table 8.3 gives learning rates estimates assumed for onshore wind from 1990 to 2000.

| Year      | LR | Comment for LR estimate choice  |
|-----------|----|---|
| 1990-1995 | 20 | High learning than average (15%) LR as upscaling to MW turbines became the trend. |
| 1995-2000 | 25 | Learning rate increases due to the higher turbine growth rate.                    |
| 2000-2005 | 15 | Turbine growth slows down. Average onshore wind energy learning rate is used.     |
| 2005-2010 | 10 | Flattening turbine size growth implies a reduced learning rate.                   |

**Table 8.3      Learning rate choices for integrated cost assessments**

Table 8.4 summarises detailed analysis results of years from 1990 for the integrated assessment. The last row of gives estimates for the learning rates which take into account the turbine price increases experienced in the 2000s.

| Year   | 1990 | 1995 | 1997 | 2000 | 2003 | 2005 | 2008  | 2010   | 2012  |
|--|------|------|------|------|------|------|-------|--------|-------|
| <b>Size Trends</b>   |      |      |      |      |      |      |       |        |       |
| Cumulative GW  | 1.9  | 4.8  | 7.6  | 17.4 | 39   | 59.1 | 120.9 | 196.63 | 254   |
| <sup>1</sup> Large <i>D</i> (m)                                  | 40   | 50   | 70   | 100  | 115  | 125  | 126   | 126    | 135   |
| <sup>2</sup> Average <i>D</i> (m)                                |      |      |      | 53   | 68   | 75   | 79    | 82     | 84    |
| <b><sup>3</sup>Parametric Model (COE in €/ MWh)</b>              |      |      |      |      |      |      |       |        |       |
| COE Low  | 89   | 73   | 55   | 43   | 39   | 37   | 37    | 37     | 35    |
| COE High   | 110  | 95   | 77   | 65   | 61   | 59   | 59    | 59     | 57    |
| COE Av <i>D</i>  |      |      |      | 67   | 55   | 52   | 50    | 48     | 46    |
| COE DD   | 80   | 66   | 50   | 39   | 36   | 34   | 34    | 34     | 32    |
| <b>Learning Curves and Average Market Trends (COE in €/ MWh)</b> |      |      |      |      |      |      |       |        |       |
| <sup>4</sup> COE Average   | 95   | 79   | 62   | 50   | 43   | 41   | 41    | 41     | 39    |
| <sup>5</sup> COE Average + DD                                    |      |      |      | 65.2 | 54.4 | 50.6 | 48.2  | 46.16  | 45.04 |
| <sup>6</sup> LR (%)  | 20   | 25   | 20   | 15   | 15   | 15   | 10    | 10     | 10    |
| <sup>7</sup> LR (%)  | 20   | 25   | 20   | 10   | -10  | -5   | 5     | 10     | 10    |

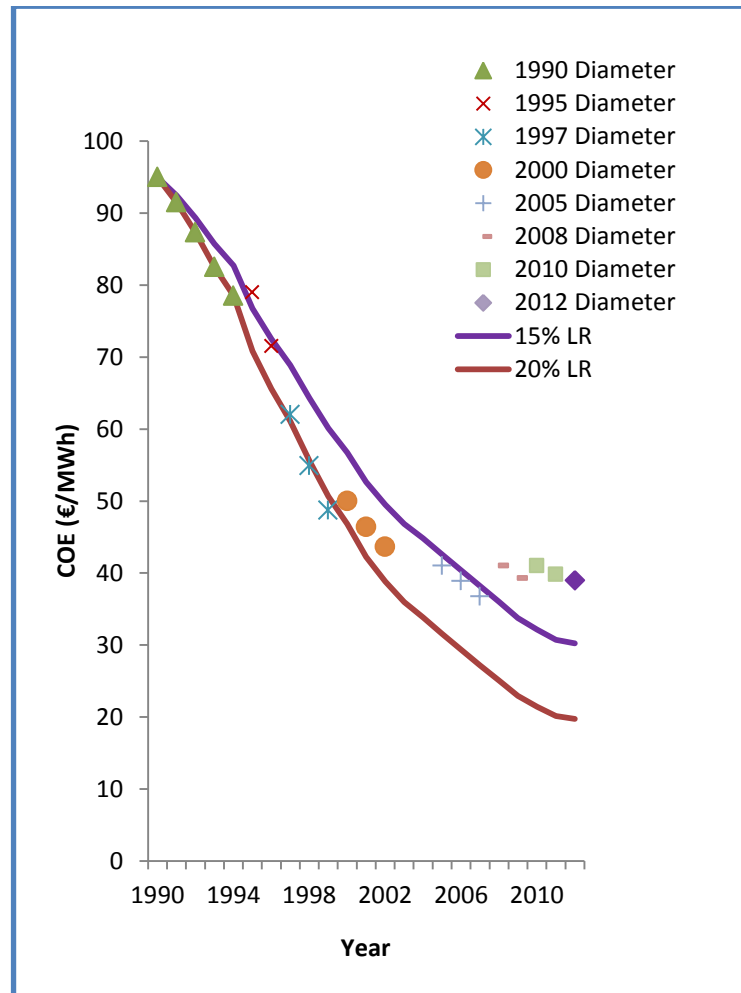
**Table 8.4 Summary of annual turbine analysis for learning curve inputs based on engineering assessments (qualitative and quantitative) and parametric modelling.**

## Notes

1. Largest turbine defined by the diameter (*D*) trending on the market for the year. See Figures 4.9 and 4.10 and. This is typically used to define turbine growth though other smaller turbine still exists.
2. Average turbine size (*D*) based on a study on US turbines. See Figure 8.12.
3. Parametric modelling results for cost of energy (COE) for low costs and high cost (standard DFIG concept), and direct drive concept (DD) based on the large size turbines.
4. COE average estimated on a market share trend of 15% DD, 50% low costs and 35% high costs from 1990 to 2000. The high and low costs are as defined for the detailed engineering assessments and the parametric models. From 2003 the market share of low cost turbines is assumed to increase by 10% due to improved turbine designs with weight reduction capabilities. The resulting market share is low cost 60%, high cost 20% and DD assumed to be 20% on average.
5. COE based on average turbine size on the market given in Figure 8.21.
6. An average constant learning rate of 15% is used in the first instance. Further analysis of historical cost reduction trends leads varying learning rates based on Table 8.3.
7. Learning rates based on assumptions made to include impact of cost and price increases for all technologies from around mid to late 2000s.

### 8.4.5 Integration Analysis Results

Figure 8.25 is a plot of the results of the integrated model based on an average market (See note 4 for Table 8.4).

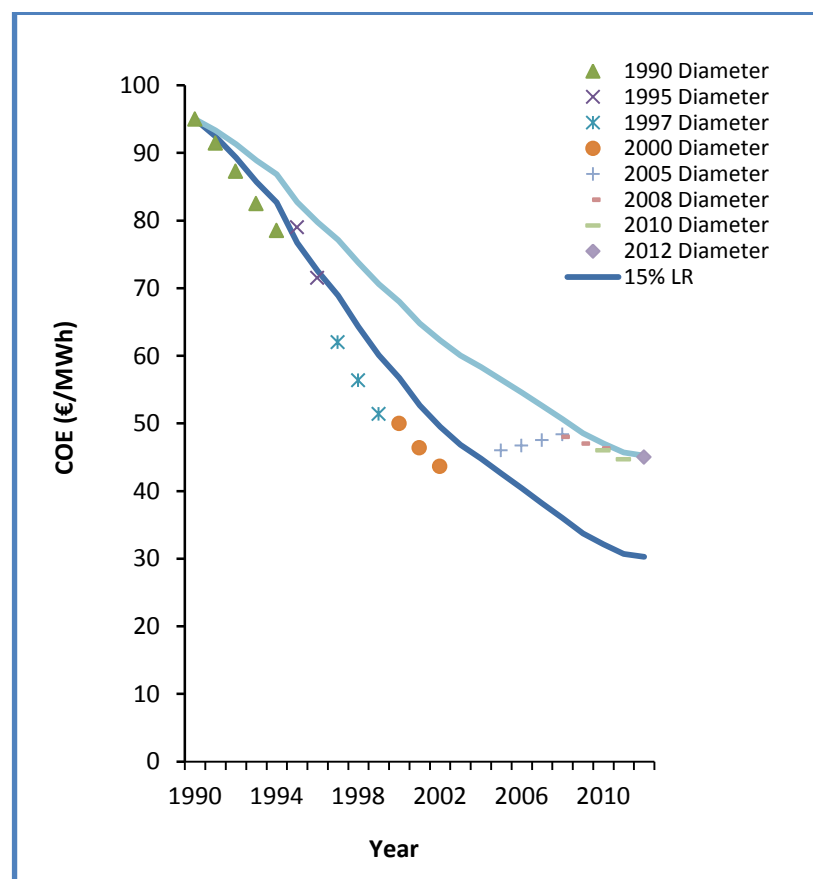


**Figure 8.25 Integration of Learning Curves and Engineering Assessments**

The results show a cost reduction trend along the 20% learning rate curve and till 1995 due to capacity growth and size increases. The costs step up to the 15% learning curve as the turbine size and installed capacity growth are not high enough to maintain cost reduction at the 20% learning rate level. This is followed by rapid growth in turbine size from 1995 to 2000 resulting in the cost trends gradually shifting down to the 20% learning curve. Thereafter, from 2000 there is a transition of learning curves as cost show a stepping-up trend due to the reduced growth in

turbine size or the flattening of the size trend as discussed before for the complementary method, and illustrated in Figure 4.9. After 2010 the curves costs appear to be shifting to even lower learning rates.

The engineering model and parametric models were based on the upscaling of turbines and the use of direct drive turbines. It is possible to similarly model the impact of other cost drivers such as the impact of economies of scale using this disaggregated approach. The main emphasis is on the need for a detailed analysis at strategic historical points to ascertain the impact of all cost drivers at the points and identify cost reduction potential relevant learning rates. For example, the increases of the 2000s can be included in the analysis using learning rate changes suggested in Table 8.4 (see note 7). The results are shown in Figure 8.26.



**Figure 8.26** Integration of Learning Curves and Engineering Assessments—Other Factors

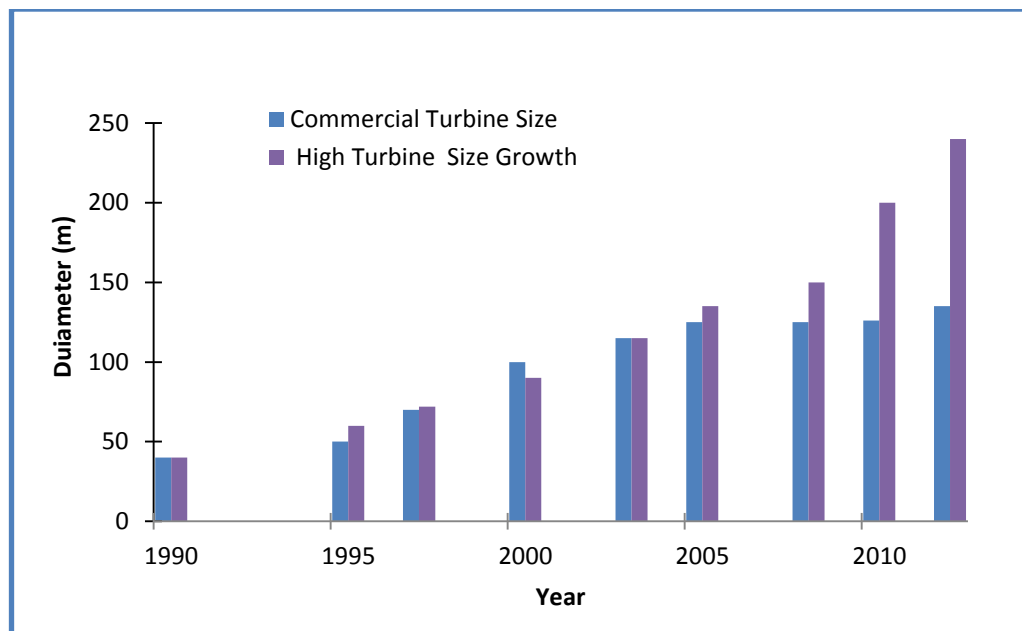


The results show an apparent step-up from 20% LR curves to 10% LR curves and cost increases from around 2003 to 2009 followed by less apparent cost reduction along the 10% learning rate curve.

## 8.5 Discussion

### 8.5.1 Sensitivity Analysis

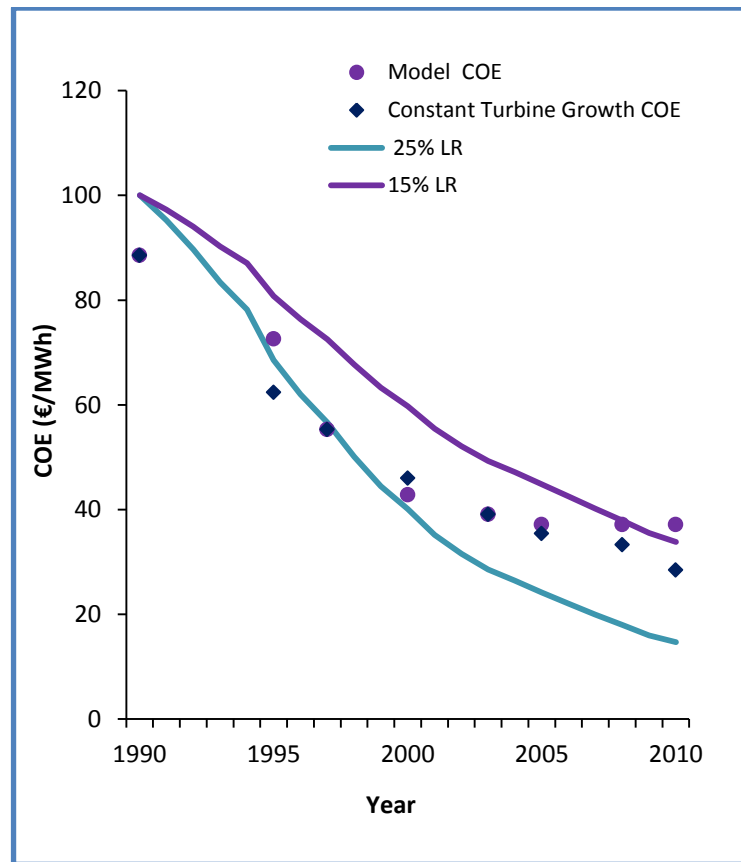
A sensitivity analysis is carried out to investigate the impact of maintaining high levels of size growth in terms of the turbine diameter, resulting in a market with relatively larger turbine shares in the 2000s than modelled before. It is assumed that from 1995 the typical levels of growth are maintained to 2010 where the size increases by 50% every 5 years illustrated in Figure 8.27 which compares with the actual turbine sizes.



**Figure 8.27 Turbine size growth –Constant growth rate**

The flattening of the turbine size growth experienced after 2000 is avoided and turbine size grows to a diameter of 200m by 2010. In reality this is achievable if the challenges associated with continued upscaling, such as very heavy turbine components and associated transportation limitations, are addressed. The resulting

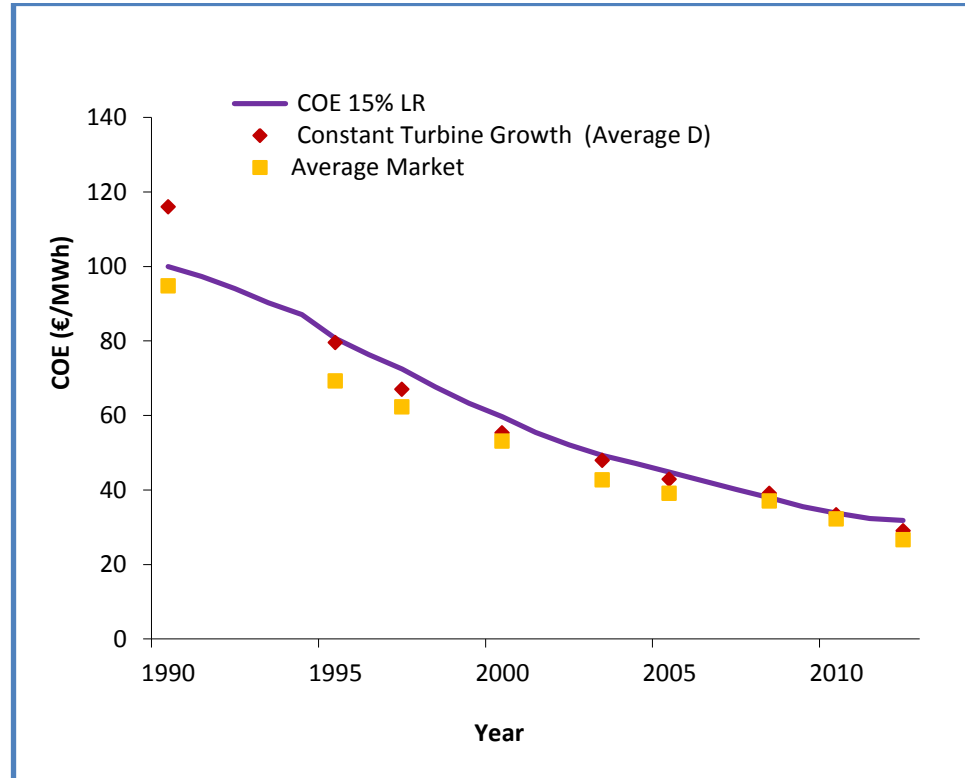
integrated model learning curves are shown in Figure 8.28 based on the largest turbine on the market.



**Figure 8.28 Learning Curves and Engineering Assessments – Sensitivity Analysis**

The constant turbine size growth in Figure 8.27 cost results illustrate a more gradual transition from 25% learning rate curves to 15%. This implies different cost reduction rates depending on the turbine diameter size. The rate of cost reduction is reduced for very large turbines due to excessive component weights compared to the scaling of smaller turbines of the 1990s. For the constant growth scenario, the flattening of the cost curve in the 2000s compared to the model curve is reduced, however, not to a large extent. This is a caveat in the continued upscaling of onshore wind turbines. An improvement of the scaling exponents used in this study is required for turbines with diameters larger than 135m for improved results of Figure 8.28 so as to gain a better understanding of the cost dynamics of very large turbines.

Again, the curves in Figure 8.28 are based on the largest size turbines. If an average market is considered by using an average turbine size which is 75% of the turbine size in the constant growth scenario or by using a market with turbine mixes with shares as described the resulting plots are shown in Figure 8.29.



**Figure 8.29 Learning Curves and Engineering Assessments for an Average Turbine Market – Sensitivity analysis.**

The resulting plots fit more closely along the 15% LR curve because of the gradual increase in turbine growth and gradual increase in installed capacity, as illustrated by the classical learning curve in Figure 8.29. This accentuates the fact that a mix of turbines of different sizes exist on the market and representation of costs for all turbines in the mix is necessary.

### 8.5.2 Results discussion

The results illustrated in Subsection 8.4.3 and 8.4.5 and the sensitivity analysis indicate that incremental changes such as the gradual upscaling of turbines are encompassed in the learning curve. COE trends plotted using upscaling models will

generally follow the shape of classical learning curves and differences are mainly in the range of learning rates. In the short term, disruptions in the cost reduction trend can be observed depending on the turbine growth. Experience result in improved ways of doing things over time. Cumulative capacity growth is incremental so is experience, in the same way turbine growth is incremental and therefore the shape of the learning curve is less likely to be affected by gradual upscaling. Learning curves therefore include incremental changes such as upscaling. However, significant cost reduction efforts for large turbines might result in step changes that alter learning curve shapes.

Changes to the shape of the learning curve will result when there are significant changes in the rate of size growth. The current slow rate of change in turbine size from the mid 2000s changes the shape and results in shifts to learning curves of lower learning rates. Moreover, the continued growth to very large turbines does not necessarily result in the same cost reduction or shifts to curves with higher learning rates due to excessive component weight and costs, thus part explaining the current reduced favor in continued turbine growth for onshore.

Upscaling also results in a market with different turbine sizes. The market share of different concepts has an impact on the learning curve shape. As the shares of larger turbines on the market increase, downward shifts to higher learning rate curves will occur. The smaller turbines installed in the 1990s which are coming to an end of their lifetime will be replaced by larger turbines.

Radical changes have the potential to change the shape and cause discontinuities. The DD COE estimated for a turbine of 80m turbine of 45 €/MWh is significantly lower than the DFIG reference turbine COE of 50 €/MWh. However, the market share of DD is relatively low. Radical change will have an impact if it is accepted on the market as a better alternative, resulting in significantly higher market shares. The introduction of cheaper novel concepts will result in more pronounced step changes in the learning curves compared to the gradual shifts caused by incremental technological changes. This might be more likely displayed when technologies are in

their early stages of maturity with no design consensus, or where a number of different concepts for the technology exist on the market such as wave technology.

### **8.5.3 Methodological issues**

The methods developed in this chapter allow the improvement of learning curves by complementing them with other cost trends such as upscaling or by reconstructing learning curves so as to take into account cost drivers that might have significant impact at some point in history. The result is the disaggregation of the learning curve depending on technological developments and their trends. This identification and quantification of cost drivers has the potential to assist in prioritising research areas and technology policy and management that promote technological developments that result in cost reduction.

It is important to find connections between experience and technological developments trends and establishing cumulative capacity for different years and levels of technological development for the respective years provides a link. In addition to technological developments, other associated cost drivers can be included in the assessment of cost for those years. Learning curve analysis will most likely benefit from the disaggregation of the curves according to significant disruptions to cost trends due to technical improvements or market related factors such the raw material increases.

### **8.5.4 Learning rates**

The complementary models results show that the COE upscaling results fit within the established range of learning rates. This supports the idea that learning curves implicitly include the majority of factors bundled in the learning rate. The main challenge is that a wide range of learning rates exists, and the credibility of approaches to both learning curve analysis and engineering assessments can be improved if the results are plotted with market data.

The wide variation of onshore wind learning rates in the literature is due to the methodological approaches to the learning curve analysis. Supported by historical

price data with good fit, learning curves describe historical cost according to the boundaries set in the studies. The geographical boundaries, timeframe and choice of independent and dependent variable types for the analysis need to be well understood, and where possible, published learning rates should be accompanied by additional information on the choice of parameters and variables used to estimate the learning rates or the cost reduction trends. Greater convergence of integrated methodological approaches to learning curves will most likely narrow down the learning rate ranges.

In addition to differences in methodological approaches discussed in Chapter 3 and outlined by Junginger (2010), the wide range of published learning rates shown in Table 3.4 might be an indication of underlying impacts such as technological innovations or other cost effecting factors. In the short term, exogenous factors such as raw material price also produce cost increases as can be seen in Figure 8.7.

Although costs might start to reduce again after a significant disruption, typically, it will take longer for the costs to reduce to levels before the reduction, as was the case in the disruptions in the 2000s. Depending on cumulative experience alone to reduce costs, after such increases, might not be adequate because with time, it takes longer for cumulative capacity to double. Other cost reduction mechanisms are necessary to continue to reduce costs so the technology remains competitive with conventional technologies. The cost and prices of wind turbines increased in the late 2000s despite having achieved levels of cumulative capacity that would imply lower costs according to the classical learning curves principles.

The forecasting of anticipated innovations and improvements coupled with the forecasting of anticipated market diffusion in terms of cumulative installed capacity play an important role in improved learning curve methods for emerging energy technologies. For wind energy technology, different scenarios need to be set up for different market shares of turbine concepts based on the understanding of the growth of the size and conceptual improvements trends such as changes in the drivetrain trends. Continued research in turbine design and manufacture of turbine focussing on

cost reduction efforts will result in the introduction of turbine improvements with more significant impacts on cost trends.

The improvement of learning curves assists the prediction of technology costs through the use of improved learning rates that account for other cost drivers. However, if there is no significant disruption to the technological developments or other cost effecting factors, a constant learning rate might be relevant. Engineering assessment methods are still required so as to ascertain more accurate values for this average learning rate that includes all cost factors.

### **8.5.5 Upscaling**

Upscaling of the turbine size has a critical impact on costs, which needs to be modelled. Currently, the turbine size trend for the largest turbine has generally levelled off for onshore wind energy technology and the large turbines in the 4 to 5 MW turbines have seen no significant changes in diameter size. It should be noted that the majority of larger turbines greater than 4 MW have been installed offshore than onshore. Lantz and Hand (2011) suggested an average largest turbine of 3.5 MW for onshore. However in Europe larger onshore turbines are in operation. For example, Estinnes windfarm in Belgium has 6 Enercon 126/6000 turbines with a power rating of 6 MW and diameter of 127m (Enercon, 2012).

Upscaling requires further innovation because on its own it has limits which might have been reached for onshore wind (Lantz and Hand, 2011). Upscaling to new large diameters of up to 150m or even 200m might be mainly for offshore, which will be discussed in the next chapter. Onshore wind turbines upscaling will continue to play an important role with the average diameters tending to increase as more turbines in the upper size range are manufactured and installed, rather than increasing the largest diameter. Generally, upscaling will be limited by excessive costs associated with very large turbine blades and towers due to the current scaling exponents, but technological improvements can reduce scaling exponents.

### 8.5.6 Extrapolating into the future

Integration of learning curves and engineering assessments should not undermine learning curves advantages, but rather improve the ability to forecast cost accurately. Unlike long term learning curves, engineering assessments are more relevant for short to medium term analysis.

Projections for the future cost of wind energy with greater precision in magnitude and likelihood will support policies that promote clean electricity supply technologies. The competitiveness of wind energy is dependent on continued innovations and technological developments that will bring cost down. Engineering based models such as those developed for this study provide the opportunity to quantify the impact of innovative concepts on wind plant system COE (Hand, 2013). Integrated approaches to assessment are therefore necessary for extrapolation into the future. When extrapolating costs, qualitative engineering methods enable the forecasting of future innovations and levels of technology diffusion in terms of installed capacity.

The link between the scaling models and learning curves over time is dependent on capacity growth. Learning curves do not predict market diffusion (Junginger, Van Sark et al., 2010), therefore methods of forecasting diffusion in the context of possible innovations are necessary. The forecasting of capacity growth is beyond the scope of this work.

The extrapolation of future costs using the proposed models would be improved if further scaling exponents are developed to account for the necessary weight reduction measures necessary for larger turbines up to 10 MW or 20 MW (Polinder, Bang et al., 2007; UPWIND, 2011). For example, larger blades will most likely be made up of carbon composites. The drivetrain will tend towards DD with permanent magnets and medium speed drivetrains with one or two stage gear boxes with improved reliability. However, increased research efforts are needed to reduce high costs of permanent magnets.



The use of integrated methods for forecasting future cost reductions would require a detailed analysis for each year to predict installed capacity, anticipated innovations and their impact on cost and any other cost drivers that can affect the cost. Engineering based qualitative and quantitative methods are sometimes used for such analyses, and parametric modelling can help simplify quantification where several alternative concepts exist. Engineering assessments therefore assist in disaggregating learning curve analysis into shorter time frames driven by possible cost effecting technological changes in addition to cumulative experience. Further improvements will allow the inclusion of non technological changes such as policy intervention and R&D efforts.

In summary, forecasting future costs is based on an understanding of:

- Possible future innovations and impact on cost
- Market shares of alternative concepts and their cost impact
- Learning rates and their possible changes
- Market diffusion or the global capacity growth
- Other endogenous and exogenous cost drivers some of which are unpredictable

This understanding and prediction should be based on assessments of historical trends as was carried out in this study for the years 1990 to 2010 which addresses the first three factors for historical costs.

## **8.6 Conclusion**

In this chapter methods were developed for improving learning curve analyses for onshore wind by integrating learning curves with the results of the engineering assessments and parametric modelling developed in the earlier chapters for onshore wind energy technology. Initially, methods were developed that allowed engineering based scaling model results to complement learning curve analysis. Thereafter, the engineering based results were integrated into the learning curves.

The complementary approach showed that the upscaling data was within the range of published learning rates. However, the ranges of these learning rates was found to be

wide and this was attributed to methodological differences in learning curves analyses and in possible underlying cost affecting factors aggregated in the learning rate. The integrated approach resulted in the disaggregation of learning curves into series of learning curves, which depend on the technological development of wind energy. Future projections using integrated methods require the prediction of not only cumulative capacity growth but of possible future technological improvements as well as other predictable factors that have an impact on cost.

The aim of the onshore wind energy case study was to assist in the development methods which are steps towards the representation of costs for an emerging technology whose continued competitiveness is dependent on innovations. Engineering assessments were used to estimate cost data for the 2 MW reference turbine, which is rarely available in the public domain. Parametric modelling was then used to modify the data to account for several changes to the reference case for alternative concepts. In this chapter, learning curve analysis was integrated with engineering assessments and parametric models data obtained from the previous chapters on these models. This resulted in the disaggregation of learning curves to account for the impact of technology improvements for onshore wind. The resulting learning curve shape was analysed it was found that with gradual incremental change, such as upscaling, the learning curve shape remained nearly similar to the classical learning the same with possibilities of gradual shifts dependent on the technological development growth. Pronounced step changes are observed if there exists radical cost impacting changes or sudden changes in incremental technological developments. Step changes can be positive step-down to higher learning rates or negative step up lower learning rates. Engineering assessments are needed in all the cases to establish the relevant costs and cost reduction potential due to the major technological and non-technological factors.

The application of methods developed in this study stands to be more beneficial for other emerging technologies such as offshore wind and possibly wave and tidal energy. Moreover, although the study focussed on the impact of technological improvements, other factors have an impact on the costs. A holistic approach would require the inclusion of more cost drivers in addition to upscaling and direct drive

concepts. The application of these approaches to include such factors, as well as for the assessment of other emerging energy technologies is discussed in the following chapter.

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## **9 Discussions and Conclusions**

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### **9.1 Introduction**

This study focussed on the problem of developing improved methods of assessing learning effects of emerging low carbon energy supply technologies and onshore wind energy technology was used as a case study for developing such methods. The study highlighted the need to understand specific cost drivers such as change brought about by particular technological improvements. The developed methods were based on the disaggregation of the learning curve so as to accommodate the impact of upscaling of turbines and the move to direct drive (DD) turbines. This chapter firstly discusses the application of the three methods in the onshore wind case study. It further discusses application of developed assessment methods to offshore wind energy, marine technologies (wave and tidal), and emerging energy technologies in general. Finally, it gives a conclusion to the thesis.

The next section 9.2 discusses the developed methods and the results for the case study and how these can improve the learning curve analysis. Sections 9.3 discusses how the methods can be used for offshore wind energy followed by Section 9.4 for wave and tidal energy technologies. Section 9.5 discusses other cost effecting factors that might need to be included in the modelling processes. The generic application of the assessment to other emerging energy technologies is discussed in section 9.6. Section 9.7 proposes further studies emanating from this thesis and the conclusion of the thesis is given in section 9.7.

### **9.2 Assessment of the Reference Technology**

#### **9.2.1 Engineering Assessment**

One of the main limitations of the learning curves is associated with the challenges in finding cost data, which typically leads to the use of price data as a proxy. Engineering assessment was used as a means for obtaining cost data for the reference

turbine. Furthermore, engineering assessments allowed the separation or disaggregation of the wind energy system and thus, identifying the main cost drivers.

The cost estimated were representations of a hypothetical project based on the assumption of a 2 MW turbine installed at Dunstaffnage, as given in Chapter 6. Real data requires a choice of a specific project as opposed to a hypothetical one. The results from the Sunderland based model sufficed as a benchmark for the analysis of the impact of change as opposed to absolute analysis with emphasis on estimating wind energy costs.

Although the Sunderland model was developed years ago, in the 1980s, it was found to be the basis for other cost and upscaling studies (Fingersh, 2006; Maples, Hand et al., 2010; Lantz and Hand, 2011; Tegen, Hand et al., 2012). There is however, need to continue to upgrade it so its relevance for modern turbines will be maintained.

The use of cost assessment models for energy converter device components that are based on the estimation of physical dimensions allows further exploration of alternative concepts. Furthermore, the use of a weight based model allows validation and comparison of concepts without using cost, which is rarely available. It does not always follow that if modelled weight data plots well with market data, cost models will be similarly good. However, if the weight model is validated, relative comparisons of costs can be carried out with greater confidence.

In addition to the weight estimations, the component costs were also based on specific costs. With the weight validated, the major source of error for the reference turbine components cost estimates would have been the specific costs. Overall specific cost estimates were used for the components accounting for all the cost elements, that is: raw materials, manufacturing (including labour and assembly of subcomponents), and all overheads. These are major cost centres with different potential for cost reduction. Detailed cost development for specific components was not the major focus of this study. To estimate absolute component cost, detailed analysis that entails isolation of the specific cost elements become a necessity.

The Vestas V80 turbine model was chosen as it is a common model and had significant amount of data. However, its suitability as a benchmark for a generic model might need to be tested by replacing it with another 2 MW turbine model from a different manufacturer such as REpower. There is a possibility that there would not be much change because the data that is made available is mainly on operational parameters where there are no major differences for turbines with the same power rating and the rest is based on calculations and assumptions. Caution is also needed when setting assumptions where data is limited and consistency needs to be maintained for relative analysis models.

Modelling COE globally is a challenge due to its sensitivity to local and project specific factors which are not necessarily typical for all countries such (Section 4.4.2). For example, China as an emerging economy with cheap labour, has different cost development trends to the rest of the world (IRENA, 2012). The cost increases in several American studies focus on turbine designs for low wind speed sites (Cohen, Schweizer et al., 2008; Wiser and Bolinger, 2012; Tegen, Lantz et al., 2013). As high wind speed areas are becoming more exploited, turbine installations move towards low wind speed regimes. Though this is a global issue, in the short term, it is not a high agenda issue in Europe which has very good wind resources. In the UK the focus is more on moving offshore.

### **9.2.2 Parametric Modelling**

Parametric modelling is based on the establishment of cost estimation relationships (CER). For this study the CER was defined as the product of the reference turbine cost and the parametric factor (PF) whose independent variable for a new turbine size is its diameter. The derivation or choice of scaling exponents and their respective shares for the turbine components as well as the balance of station element underpins parametric modelling. The scaling exponents were derived from the models used for the Sunderland based detailed model. The shares for the scaling exponents and turbine components were derived from the reference model costing results.

The validity of the results was dependent on the credibility of the parametric model which in turn largely implies development of scaling exponents. The idea of the

development of the scaling exponents which were not just cubic or square functions as in previous studies was a new contribution of this study. Scaling models have been used, but the author could not find evidence of improved scaling exponents developed and defined using a simple factor parametric factor (PF) used to simply parameterise the reference costs to account for size differences. This contribution simplifies the exploration of alternative turbine models and the quantification of their cost impact. For example, equation 9.1 gives the parametric for the installed capital cost for a DFIG turbine with diameter  $D$ .

$$PF(D) = 0.026r^{1.10} + 0.037 + 0.434r^{2.00} + 0.036r^{2.35} + 0.007r^{2.50} + 0.013r^{2.60} + 0.039r^{2.64} + 0.154r^{2.70} + 0.027r^{2.88} + 0.229r^{3.00} \quad 9.1$$

The variable  $r$ , is the ratio between the turbine size at any diameter and the reference turbine whose cost values are known and is given by  $r = D/D_{ref}$ . The equation has proven valid for any turbine with size  $D$  within a range which was set between 40m to 135m provided the major change in the turbine is just the size. Other significant change would call for changes in the exponents or the shares of the exponent. Radical changes might require changes in the reference turbine values as was the case with the direct drive (DD) turbine.

The parametric factors for the CER are highly sensitive to the choice of scaling exponents. Effort is therefore required to develop relevant exponents. As the turbine is upscaled to very large diameters, there might be need to upgrade or redefine the scaling exponents. Upscaling in the absence of innovation has led to increased costs (Lantz and Hand, 2011).

### 9.2.3 Integrated Learning Curve Analysis

The results of the combined modelling where the upscaling results were plotted with learning curves showed that the results lied within the range of learning rates in literature. However, these learning rates have wide ranges and their use has been associated with limitations as discussed in Chapter 2. The integrated approach managed to disaggregate the onshore wind energy learning curves based on a constant learning rate enabling the inclusion of the impact of upscaling and on

innovative drivetrain. The ways in which the proposed methods attempt to tackle the major limitations in the use of learning analysis approach are given below.

### *1. The Aggregate Nature of the Learning Curve*

The process of disaggregating learning curves in Chapter 8 isolated the cost drivers. In this particular case, the impact of upscaling and the move to direct drive were analysed and quantified. The possibility of decentralising the starting point from just one point in 1990 to several points allows the explicit inclusion of other factors. The integrated approach is supported not only by quantitative engineering assessments or parametric modelling, but also qualitative engineering assessments that allows the identification of trends and their projection into the future.

### *2. Data availability and early cost estimates*

The detailed engineering based costing in Chapter 5 and 6 allowed the derivation of cost data for the 2 MW reference turbine which was used in the learning curve analysis. Technologies such as onshore wind energy are complex and detailed modelling can be resource consuming. The advantage of the engineering assessment methods used in this study is that the detailed analysis is only used for the 2 MW reference turbine and parametric methods are used to derive costs of turbines with different configurations. For the radical direct drive configuration, the disaggregation of the turbine into subsystems enabled simpler costing of a new reference with a direct drive thus improving data methods. The ability to parameterise costs can assist costing in the early stages of development allowing for changes in cost. This has the potential of improving data methods for learning curve analysis for early stage technologies before they stabilise on the market.

### *3. Cost Increases (negative learning)*

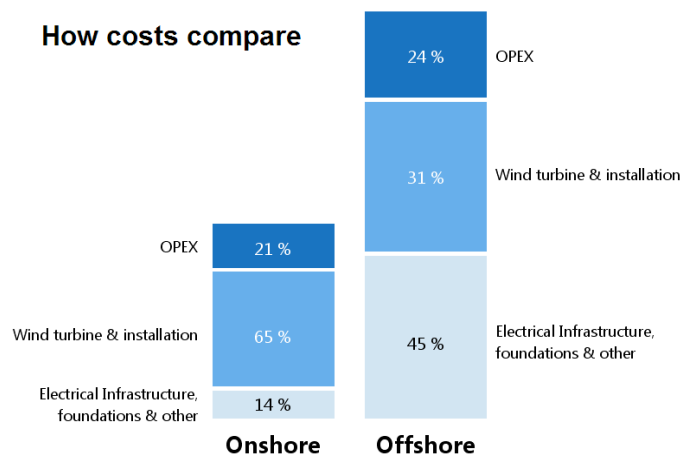
The ability to analyse cost trends at different points in time allows the factoring in of possible changes in cost trends in the short term. It was possible to include the impact of the cost increases in the mid to late 2000s as experienced for wind energy capital costs as well as for the cost of energy (Figures 8.1 to 8.4). This period had



negative learning rates, which are not represented by classical learning curve theory. Average learning rates overshadow such occurrences and disruptions, which might have impacts in the medium to long term. The methods developed in the previous chapter can assist in the modelling of negative learning rates.

### 9.3 Modelling Offshore Cost Trends

As mentioned in chapter 4, offshore wind energy is a more emergent energy technology compared to onshore. There has been significant commercial activity since the early 2000s. The turbine design configurations for offshore nearly similar to onshore turbines, only adapted to handle marine environments (Fingersh, 2006). Offshore turbines require improved foundations for installations in water compared to the land based foundations. Transportation costs are also relatively higher because of the vessels required for transportation to the windfarm. These costs are highly dependent on the distance from the coast. The high offshore costs are partly offset by high energy yield, but even so the cost of generating electricity at sea can be as high as twice the cost onshore. For example, in the UK in 2011, windfarm projects assessments indicated costs stabilising around £140/ MWh and cost reduction pathways to 2020 were developed with targets to achieve £100/ MWh (Arwas, Charlesworth et al., 2012). Figure 9.1 compares onshore and offshore cost shares.



**Figure 9.1 Onshore and offshore Capital Costs (Coulter, 2012)**

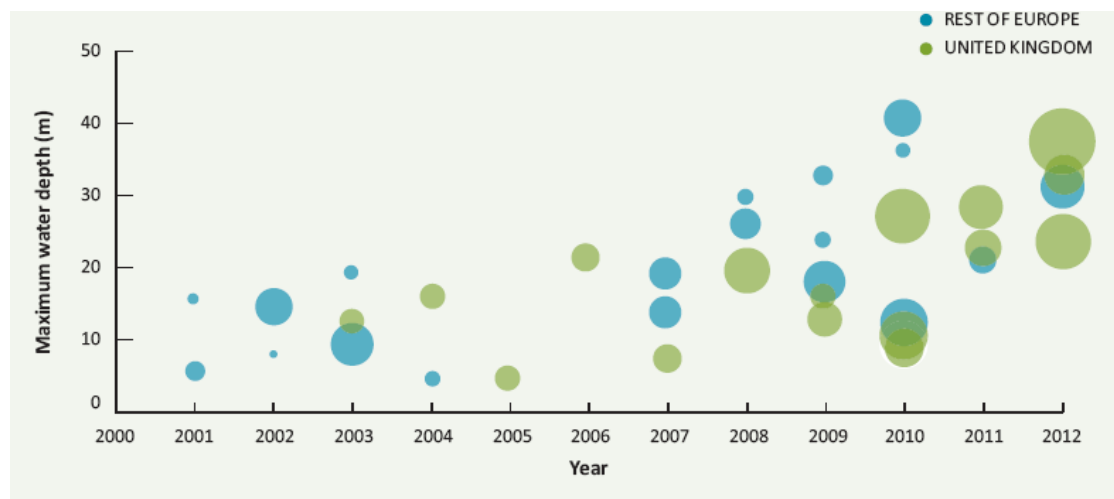
The turbine costs constitute a lower proportion of offshore costs compared to onshore costs. Offshore BOS costs are high due to foundation and transport costs.

Offshore cost data is limited and reflects uncertainties in the sector, hence future projections must be viewed with caution (Arup, 2011).

## Offshore and Upscaling

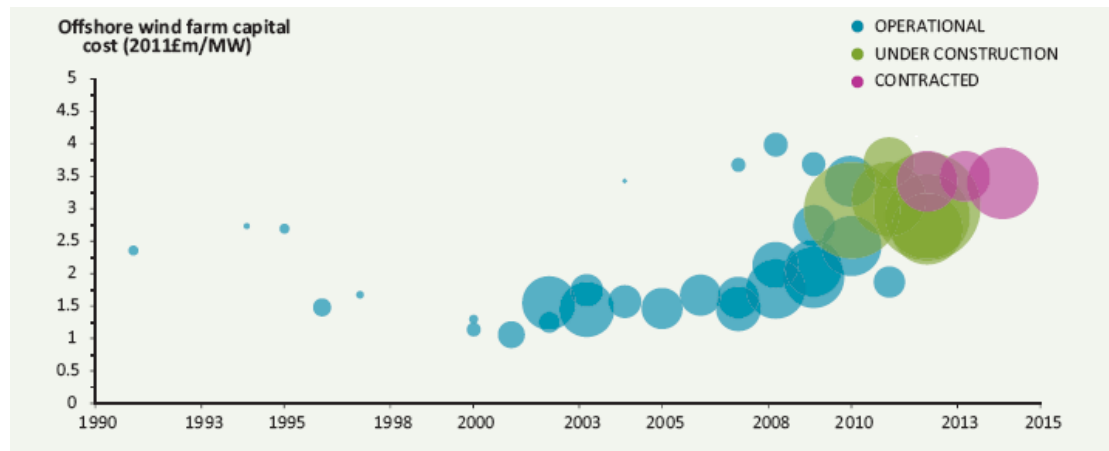
The capital cost increases due to upscaling have the greatest impact on the turbine costs compared to BOS and O&M costs as demonstrated by their scaling exponents in Table 7.6. For the parametric model, the scaling exponents of the turbine were found to be between 2 and 3 whereas the scaling of BOS components was 1.1 or less. Onshore turbines constitute a very large proportion of about 65% compared to 30 to 40% for offshore as illustrated in Figure 9.1. Consequently the impact on overall capital costs, even more so on COE will be advantageous for offshore with a relatively lower turbine cost share and a high BOS cost share. Moreover, the increased energy capture for offshore will further help reduce scale associated COE. Upscaling will therefore continue to be favoured for offshore applications.

The parametric model for offshore wind COE requires upgrading to account for the reduced turbine share but more upgrading is required to account for the changes in the BOS costs in particular foundation costs and transportation costs. In addition to technological improvements such as incremental upscaling, one possible area where impact needs to be assessed is the move to deeper waters. Figure 9.2 shows the trend for offshore for UK and the rest of Europe.



**Figure 9.2** Offshore turbines water depth trends (Arwas, Charlesworth et al., 2012)

Water depths have increased from less than 10m in 2000 to depth of up to 40m in the recent years. The balloons in the figures represent the relative installed capacity at the depth. Figure 9.3 shows the of capital cost trends for European windfarms.



**Figure 9.3 European Windfarm costs by year (Arwas, Charlesworth et al., 2012)**

Increases in capital costs have been attributed to the move to deeper waters among other factors. At the same time the move to deeper waters further offshore with higher undisturbed winds result in increased energy capture. The assessment of the overall impact of the move to deeper waters can benefit from the developed parametric modelling methods. The benefit of the move would be realised using COE comparisons and integrating in the learning curves analysis would help in proposing technology pathways that maximise cost reduction and hence improved support of offshore wind. The analysis would involve establishing a relationship between capital costs and water depth or foundation costs and water depth. The move to deeper waters requires improvements in the foundation and this might imply exploration of different foundation concepts.

## 9.4 Modelling Wave and Tidal Costs

Wave and tidal energy technology are relatively in their infancy stages, lacking operational experience with no design consensus and relatively few devices are at commercial stage compared to wind energy (Callaghan and Boud, 2006). From the wave energy case study (Mukora, Mueller et al., 2008), and review of literature on energy technologies learning curves, the application of learning curves to marine

technologies is limited (Junginger, Van Sark et al., 2010; Jeffrey, 2008). However, it has similarities with wind energy and the principles used to develop methods of assessment for the case study can be adapted for marine energy. As mentioned in Chapter 2 wind and marine energy technologies are mainly based on the conversion of mechanical energy to electrical. Similar to wind energy in its early stages in the 1980s and 1990s, wave and tidal costs are currently high but have opportunity to come down although the wind turbine design diverged at a faster rate to the “Danish concept”.

It is anticipated that installed capacity will grow in countries with wave and tidal, resource potential where there are opportunities for cost to come down with research, deployment, experience and continued innovation. Currently R&D policy both government and private initiatives play an important role. The assessment of wave energy through the use integrated learning curve methods for marine energy therefore needs to the impact of R&D efforts.

Due to the lack of design consensus, engineering assessment would require the identification of not only reference device but common elements as suggested by Stallard et al. (2008). Identification of similar components to simplify detailed models and make analysis comparable. Parametric modelling would aim at analysing different devices and then impact of possible technological changes brought by innovation. Cost estimation relationships would need to be derived which compare and cost different devices based on common elements such as. These might be related not only to physical attributes, but to the performance or reliability of the devices. Different scenarios are then set for a market with the devices and these are then integrated with learning curve methods. Where learning curves are limited, analogous methods are used. This approach would allow the analysis of the impact of design changes on cost and could assist in the choice of devices with attractive short as well as long term cost reduction potential.

The use of the integrated methods for marine energy would need more adaptation from those developed in the study than for offshore. However, parametric methods and engineering cost methods can be more applicable. With more understanding of

the cost driver of the cost, current learning curve methods of onshore wind, offshore, wave, tidal and other energy technologies can be improved by disassembling their learning curves at strategic points to include the cost drivers.

## **9.5 Other Cost Drivers**

This section looks at other cost factors that might be overlooked in learning curves or are excluded and would require to be considered in further model upgrades. As a technology gains experience, the knowledge of what is involved in producing or using it and how to reduce costs leads to improvements in design and manufacture, reduced time to deliver and lower labour costs. For low carbon energy supply technologies investor confidence as well as policy maker support improves as the deployed technologies gain experience. The learning curve is a representation of all these cost factors and has been used to represent overall cost reduction. However, a better understanding of these sources of costs through the identification of the significant cost centres will result in improved presentation of the costs of emerging energy technologies. The possibility of disruptive changes in cost centres in the short to medium term has the potential to reduce the validity of predicted learning rates. Understanding the impact of technological improvements as well as other cost effecting factors can help in the identification of those factors not included in the learning curves analysis. The analysis of the factors discussed below can enhance the further understanding of long term cost trends and cost dynamics in the short term.

### **9.5.1 Turbine Design and Manufacture**

Manufacturers use design and manufacturing strategies aimed at minimising costs and increasing performance of a product to maintain competitiveness. Weight reduction measures have allowed the manufacture of turbines of larger diameters at the same rated power that maximise on energy capture. The V90m Vestas turbine with a diameter of 90m and rated power of 2 MW weighs the same as the Vestas V80 at 80 m. Weight reduction reduces scaling exponents for the parametric model. Standardisation and design simplification reduces the number of parts and assembly costs which in turn reduce the turbine costs.

Turbine components are mainly either specialised or off-the shelf. Off-the shelf components such bearings are used elsewhere and are typically cheaper than specialised components such as turbine blades. However, for some components specialised components specific to the turbine market are ideal and can be optimised for the purpose. As the market increases and experience is gained the cost of specialised components reduces.

Manufacturing strategies lead to production efficiency improvements resulting in mass production and economies of scale (Arwas, Charlesworth et al., 2012). The acquisition of some leading manufacturers by other manufacturers such as the case of Suzlon acquiring REpower might have an impact on global costs. As the market enlarges, companies invest in specialised plants targeted for large turbine components. The presence of Chinese companies in the global top ten original equipment manufacturers (OEM), where labor is cheap might have a major influence on turbine costs in the future. As the wind turbine technology market matures, new products take reduced time to be introduced on the market. The innovative drivetrain concepts will take less time to compete on the already established market. New market entrants find reduced barriers to entry and this stimulates competition and results in cost reductions.

Supply chain constraints and bottlenecks can result in unforeseen cost increases (Bolinger and Wiser, 2012). To cope with the continuing uncertainty of supply, some turbine manufacturers decide to vertically integrate and produce more of their components in-house. Of the leading manufacturers, Enercon and Gamesa have historically produced all their main components within their own business structure. After the earlier purchase of gearbox manufacture Hansen, Indian company Suzlon was also vertically integrated (Aubrey, 2007). GE, on the other hand, has outsourced more, including its blades, considered by many to be the most vital component. Outsourcing raises issues not just of secure supply, but of quality control and design confidentiality (Aubrey, 2007).

Modelling the overall cost impact of manufacturing cost changes such as manufacturing efficiency improvements requires isolation of manufacturing costs

from specific costs estimations. The specific costs are disaggregated to identify specific cost centres such as materials, labour and overheads. It is important to carry out further investigation of the impact of manufacturing on the costs and understand the impact of efficiency in manufacturing.

### **9.5.2 Market**

Cost reduction will depend on market demand and market enlargement (Junginger, Van Sark et al., 2010). Governments create a market for renewable energy technologies based on cost reduction assurances (Arwas, Charlesworth et al., 2012). On the other hand, cost reductions are dependent on a predictable market that allows cumulative production. This conflict can be solved by integrated assessment methods that are based on an understanding of market diffusion in the form of cumulative installed capacity and cost reduction potential that is enhanced by technological advancements and other cost reducing factors. Sudden increases in demand however, can cause supply shortages that will result in component prices to increase and hence turbine cost to increase. Moreover, if capital cost increases are not balanced out by increased annual energy production, COE might also go up as was the case in the early 2000s for most energy technologies.

### **9.5.3 Policy and National Issues**

The support of sustainable energy in the forms of subsidies and policy that encourage deployment will continue to help create markets for emerging energy technologies, which in turn will result in reduced costs in a well balanced supply and demand market. Energy policy varies for different countries, but international and regional agreements such as the EU 2020 carbon emissions targets have a role in the achievement of global cost reductions. Wind energy costs are also relative to costs of the conventional sources. Wind energy costs in 2010 were reported generally stable and likely to fall, whereas fossil fuel prices were rising (Milborrow, 2010). Improved methods for including externalities and carbon pricing in the assessment of COE of early stage low carbon energy supply technologies are required.

The overall economic condition, both global and local has an impact on the cost and price of wind energy. Issues affecting the company as well as the country and the world that impact the technology need to be considered. Due to the growing market in China, it experienced larger levels of cost reduction than other countries. With a large global share of the market and installed capacity, the cost trends in China are likely to influence the global trends and the cost estimates for the technology. Other factors include foreign exchange rates and interest rates which vary between different countries (Bolinger and Wiser, 2012).

The cost drivers discussed above are typical for emerging energy technologies and the application of the methods that were developed using the onshore wind energy technology case study are discussed below for emerging energy technologies in general.

## **9.6 Generic Modelling of Emerging Energy Technologies**

The conditions necessary for continued competitiveness of emerging energy technologies are a combination of the need for deployment in an enlarging market leading to growth in cumulative capacity together with incremental innovation. As discussed in Chapter 2, the use of learning curve analysis for emerging energy technologies which typically have limited data need technological improvements and innovation. The more emergent the technology, the greater the need for technological improvements and other cost reduction measures hence the greater the need for improved learning curve analysis methods. Technologies such as wave energy do not have design consensus such as the case of the onshore turbine and assessment methods can be used to compare different concepts other than just changes to the concept (Mukora, Mueller et al., 2008). Not all technologies scale in terms of the device size such as the wind turbine diameter, but in terms of the project size.

Generic methods are based on establishing standard methods to forecast the future of technology costs in a way relevant to their characteristics. Such methods can provide means of explaining variabilities in cost reduction trends due to different cost drivers which if not given proper attention can deter deployment of a technology. The understanding of cost drivers enables strategic decisions for managing and



controlling them (Coulter, 2012). Learning curves have been understood to be based on observed patterns of market diffusion, but are not capable of predicting this diffusion (Junginger, Van Sark et al., 2010). The assessment of market growth rates for learning curves is essential for future predictions (Neuhoff, 2008). The uncertainties associated with future of early stage technologies result in the development of different future scenarios and technological pathways requiring relative analysis based assessments.

Table 9.1 gives the characteristics of emerging energy technologies and the relevancy of integrated approach to their assessments.

| <b>Emerging Energy Characteristics</b>                                | <b>Challenge</b>  | <b>Solution</b>  |
|---|---|--|
| Currently expensive with potential to reduce costs                    | Quantitative representation of future costs                     | Model uses improved learning curve forecasts predicting cost reduction   |
| Relatively new  | Limited cost data for learning curve analysis                   | Detailed engineering costing methods to provide cost data                |
| Innovation plays a role in costs down therefore possible cost driver. | Learning Curves do not account for change brought by innovation | Parametric Model quantifies impact of technological improvements         |
| Prone to impact of cost drivers other than experience                 | Learning curves aggregate and do not isolate cost factors       | Learning curve disaggregated at strategic points. Engineering assessment |

**Table 9.1 Generic modelling for emerging energy technologies**

The following summarises the steps in learning curves analysis for emerging energy technologies integrated with engineering assessments.

1. Detailed cost assessment of a technology to benchmark using available data and cost engineering methods based on theory and reference to technology physical attributes.
2. The development of simple cost estimation relationships (CER) that relate the technology's physical attributes and cost and then derivation of parametric factors that can be used to account for changes in different concepts.

3. Identification of trends in terms of technology market diffusion of cumulative production or cumulative installed capacity over the year.
4. Plotting the costs estimated using engineering assessments and parametric modelling on the same graphs plot with learning curves.
5. Integrating the results of engineering based models with learning curve data resulting in possible changes to the learning rate (LR) and/or start point values ( $C_0$  and  $q_0$ ).

The cost impact of other factors such as the use of lighter materials will vary and detailed qualitative and quantitative engineering analyses are required at strategic points along the timeline of the technology diffusion for estimating learning parameters at each of the points, resulting in a series of learning curves. These are points in time where the technology has experienced significant incremental or radical change with an impact on the costs. Engineering assessment approaches are used to cost reference technologies for benchmarking any other subsequent technology costs and parametric modelling is then used to adapt these reference costs to account for incremental changes caused by all cost drivers at each of the points in history.

Radical changes might require further detailed cost analysis in part for those technology cost components radically affected. A series of learning curves are then constructed at each of the strategic points using data from engineering assessments and parametric modelling. Qualitative analysis that identify cost reduction pathways and potential in the context of all the cost factors assist in the identification of learning rates for a series of learning curves. The projection of these curves is informed not only by the cumulative capacity growth projections, but also by anticipated technological improvements and any other foreseen future cost dynamics due to major cost drivers such as those discussed in section 9.5. The resulting shape of the overall learning curve resulting from this integrated approach is more informative for analysing historical trends and predicting the future potential of the technology compared to a simple learning curve.

## 9.7 Further studies

The methods proposed and used for this research study are upgradeable and extendable can be improved at different levels. With improved data methods the validity of the results can be improved. It would be beneficial if the resulting models can be plotted with global or representative market cost or price data to observe the fit. The engineering assessment methods and parametric model can benefit from the further development of the Sunderland model to take into account innovation and changes to the reference turbine in line with the representative commercial turbines on the market. This study introduced new scaling exponents for most of the onshore wind turbine components derived from the design of the components. These exponents can be further developed to increase relevancy with design changes. With improved data such as turbine size and balance of station costs and other costs such as those discussed in Section 9.5, the disaggregation of the learning curve can be further improved for onshore wind energy technology and further for other technologies.

Further work from this study might include quantitatively assessing the cost impacts of upscaling and direct drive turbines on offshore wind costs as discussed in section 9.3. This will be based on detailed analysis of offshore cost trends and market diffusion. The upscaling to turbines greater than 5 MW will tend to be offshore application and this will require incremental and radical changes to overcome challenges associated with very large turbines. Consequently, parametric models for offshore will require the redevelopment of relevant scaling exponents. As discussed earlier, another area of study is the impact of the move towards deeper waters where energy capture is higher. Further development of methods could lead to the application to wave and tidal energy technologies as discussed in Section 9.4, and some of the methods could be used for solar photovoltaics and bioenergy.

## 9.8 Conclusions

This study sought to develop improved methods for learning curve assessment thought the use of engineering assessments methods. Chapter 1 gave an introduction to the study giving aims and proposed outcomes as well as limitations to the study.

Chapter 2 gave a review from existing literature on learning curves in the context of emerging energy technologies in the wake of global energy challenges. The chapter also looked at other methods of assessment in particular detailed engineering assessment and parametric modelling. Chapter 3 looked at previous studies and case studies where learning curves have been applied to emerging energy technologies in their simple form or combined with engineering assessment based methods or other relevant methods. The chapter highlighted limitations in the existence of integrated methods necessary for early stage technologies. It also concluded that the proposed generic modelling required initial choice of a technology as a case study.

Chapter 4 gave background information on the chosen case study technology, onshore wind energy. Wind turbine components were introduced before an overview of technological and cost trends. Chapter 5 introduced engineering weight assessment of a disaggregated wind turbine based on the Sunderland model. The 2 MW reference turbine was defined based on the commercial Vestas V80 2 MW turbine. Chapter 6 used the modelled weight results to estimate wind turbine costs. The installed capital costs (ICC) were estimated by including balance of station (BOS) costs. Ultimately, the cost of energy (COE) of the 2 MW reference turbine was estimated by including O&M cost estimates, finance factors and the anticipated annual energy production AEP.

In Chapter 7 parametric models were developed to estimate cost changes due to incremental upscaling and disruptive direct drive drivetrain methods for upscaling the 2 MW reference turbine. The results of the engineering assessments and parametric modelling were integrated in the learning curve analysis in Chapter 8, resulting in improved learning curve analysis methods based on the disaggregation of learning curves at strategic points, so as to account for significant cost changes due to innovation and other technological improvements. These approaches are steps towards the inclusion of other endogenous and exogenous factors for emerging energy technologies.

The study managed to address the research problem of developing methods of improving learning curve assessment for early stage low carbon electricity supply

technologies. Detailed engineering assessments were performed for onshore wind based on a reference turbine and parametric models were developed to simplify the projection of these costs for accounting for configuration changes brought about by innovation. The parametric models were based on the derivation of scaling exponents that described the cost trends as the turbine diameter incrementally scaled. Radical change was also considered by modelled cost of direct drive (DD) turbine costs. Cost data from these two methods was then plotted together with learning curves to observe the shape and determine relevant learning rates. Finally, engineering based cost data projected using parametric modelling was then used to develop improved learning curves in an integrated approach. The process involved disaggregating the turbine introducing discontinuities at points where there was significant technological development.

The results of the study illuminate the impact of key cost drivers typically not addressed in simple learning curves. The impact of innovation such as the upscaling and the move to direct drive (DD) larger turbines has short term impacts on cost which properly understood and managed can result in long term cost reductions. The cost trends due to upscaling plotted with learning curves and were seen to lie within the range of the learning rates in the literature. However, because of the wide range of the learning rates, the upscaling results were integrated with the learning curves resulting in a single assessment model. This brought about an improved understanding of the shape of the learning curve. The further use of the methods was illustrated through their use for onshore wind energy costs to accommodate capital cost increases in the 2000s and a step-up to lower learning rates exhibiting negative learning was represented in the learning curves.

Overall, this study made a significant addition to knowledge for wider research on costing wind energy in developing parametric models for costing onshore wind using improved scaling exponents for wind turbine component weights, instead of the frequently used simple exponents based on the cubic-square functions. The exponents were derived from the detailed Sunderland based engineering assessment models for major turbine components and subsystems. Balance of station (BOS) scaling exponents were also developed from engineering cost assessment models.

Parametric factors enabled the projection of costs in a simplified, but credible way for a wide range of turbines enabling exploration different concepts for the learning curve analysis. Additionally, this study made another a major contribution for wider research in the cost assessment of emerging energy technologies by introducing the idea of the disaggregation of learning curve where necessary, in way that preserves the advantages of using single learning rates for technologies. Disaggregation is only performed for strategic points in time where major technological development is observed, leading to a transition to a new learning curve.

The results from the integrated models indicate apparent shifts to lower and higher learning curves for incremental changes depending on the impact of the change and step changes step-changes resulting from radical changes and sudden changes in incremental technological developments. This is not modelled in classical learning curves, but the learning curve analysis can be improved through the use of methods developed in this study. This enhances learning curves' ability to inform energy systems modelling leading to the development of technology pathways with high cost reduction capabilities. Further upgrading of these methods was proposed for detailed analysis of offshore cost developments and further development can extend this work to marine technologies (wave and tidal).

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## Appendix

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Electronic copies of the following published papers can be found in the accompanying CD:

- Mukora, A., M. Mueller, M. Winskel and H. Jeffrey (2008). Wave Energy Technology Review: Application of the Learning Curve Concept 1970 – 1999. World Renewable Energy Congress X, Scottish Exhibition & Conference Centre, Glasgow.
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